Part 4: High Dimensional, Graphs and Trees, User Studies

Information Visualization Mini-Course
TECS Week 2008

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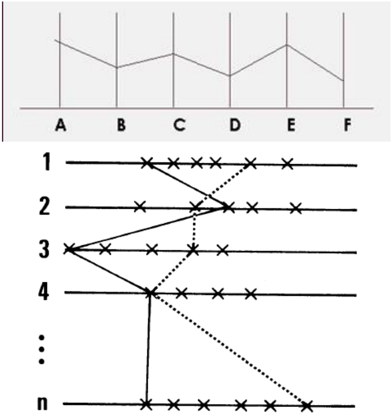
Mini-Course Outline

- Part 1: Monday morning
  - Intro
  - Design Studies
  - Models
  - Perception and Memory
- Part 2: Monday afternoon
  - Color
  - Space, Layers, and Ordering
  - Statistical Graphics
- Part 3: Thursday afternoon
  - Multiples and Interaction
  - Navigation and Zooming
  - Focus+Context
- Part 4: Friday morning
  - High Dimensional Data
  - Graphs and Trees
  - User Studies

Parallel Coordinates

- only 2 orthogonal axes in the plane
- instead, use parallel axes!



[Hyperdimensional Data Analysis Using Parallel Coordinates. Edward J. Wegman. Journal of the American Statistical Association, 85(411), Sep 1990, p 664-675.]

PC: Correllation

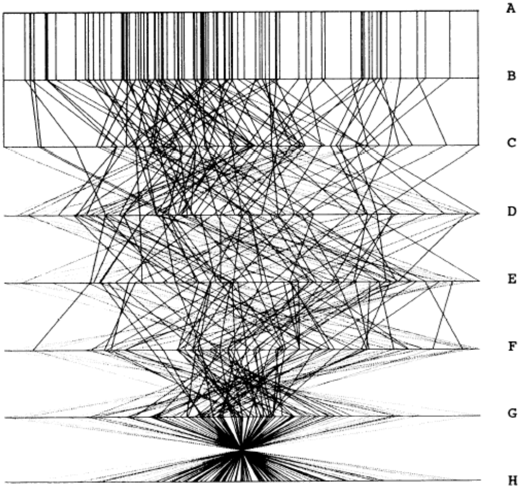
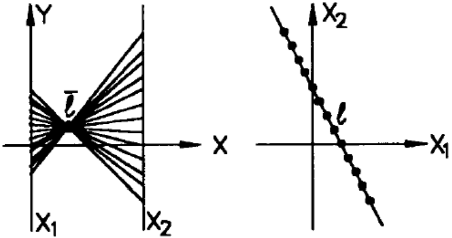


Figure 3. Parallel Coordinate Plot of Six-Dimensional Data Illustrating Correlations of $\rho = 1, .8, .2, 0, -.2, -.8$, and -1.

[Hyperdimensional Data Analysis Using Parallel Coordinates. Edward J. Wegman. Journal of the American Statistical Association, 85(411), Sep 1990, p 664-675.]

PC: Duality

- rotate-translate
- point-line
  - pencil: set of lines coincident at one point

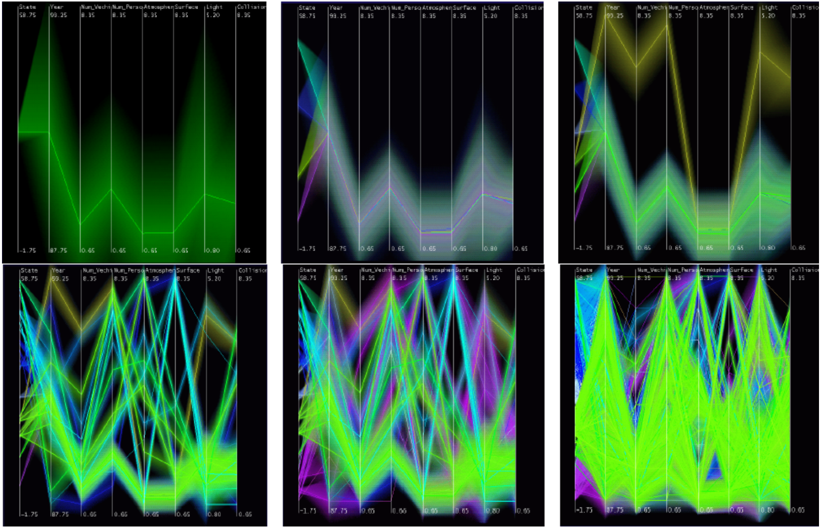


[Parallel Coordinates: A Tool for Visualizing Multi-Dimensional Geometry. Alfred Inselberg and Bernard Dimsdale, IEEE Visualization '90.]

PC: Axis Ordering

- geometric interpretations
  - hyperplane, hypersphere
  - points do have intrinsic order
- infovis
  - no intrinsic order, what to do?
  - indeterminate/arbitrary order
    - weakness of many techniques
    - downside: human-powered search
    - upside: powerful interaction technique
- most implementations
  - user can interactively swap axes
- Automated Multidimensional Detective
  - Inselberg 99
  - machine learning approach

Hierarchical Parallel Coords: LOD



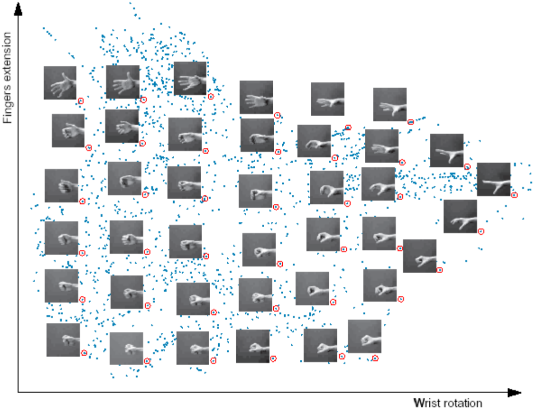
[Hierarchical Parallel Coordinates for Visualizing Large Multivariate Data Sets. Fua, Ward, and Rundensteiner, IEEE Visualization 99.]

Dimensionality Reduction

- mapping multidimensional space into
- space of fewer dimensions
  - typically 2D for infovis
  - keep/explain as much variance as possible
  - show underlying dataset structure
  - multidimensional scaling (MDS)
- MDS: minimize differences between interpoint distances in high and low dimensions

Dimensionality Reduction: Isomap

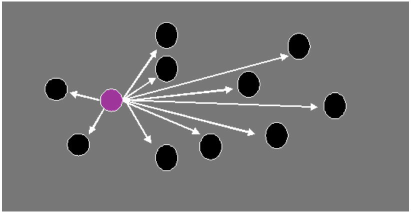
- 4096 D: pixels in image
- 2D: wrist rotation, fingers extension



[A Global Geometric Framework for Nonlinear Dimensionality Reduction. J. B. Tenenbaum, V. de Silva, and J. C. Langford. Science 290(5500), pp 2319–2323, Dec 22 2000]

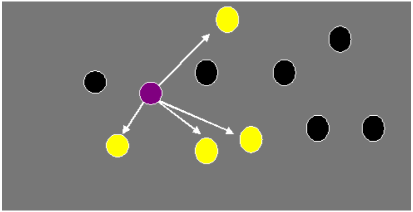
Spring-Based MDS: Naive

- 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



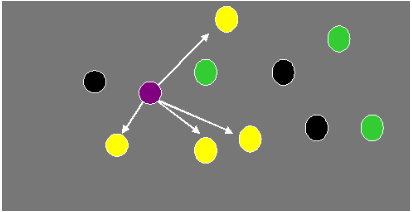
Faster Spring Model [Chalmers 96]

- compare distances only with a few points
  - maintain small local neighborhood set



Faster Spring Model [Chalmers 96]

- compare distances only with a few points
  - maintain small local neighborhood set
  - each time pick some randoms, swap in if closer



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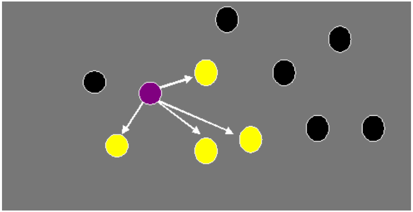
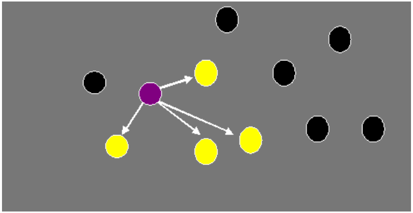


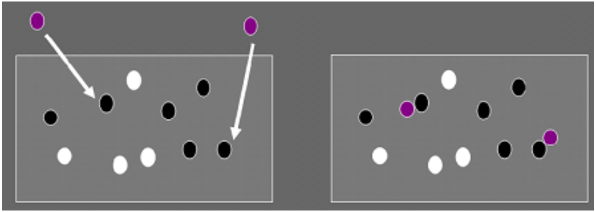
Faster Spring Model [Chalmers 96]

- 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 typical
  - $O(n)$ iteration, $O(n^2)$ algorithm



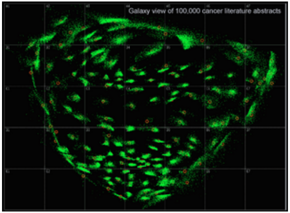
Parent Finding [Morrison 02, 03]

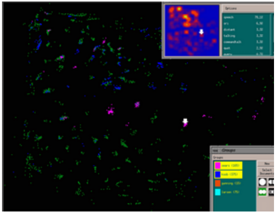
- lay out a $\sqrt{n}$ subset with [Chalmers 96]
- for all remaining points
  - find ”parent”: laid-out point closest in high D
  - place point close to this parent
- $O(n^{5/4})$ algorithm



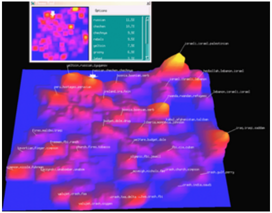
MDS Beyond Points

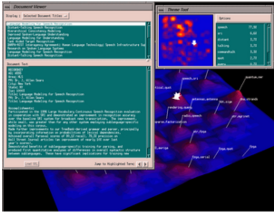
- galaxies: aggregation





- themescapes: terrain/landscapes





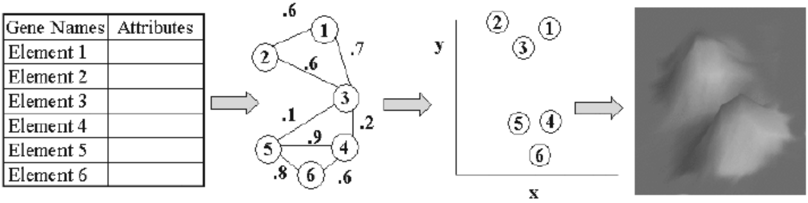
[www.pnl.gov/infoviz/graphics.html]

Cluster Stability

- display
  - also terrain metaphor
- underlying computation
  - energy minimization (springs) vs. MDS
  - weighted edges
- do same clusters form with different random start points?
- ”ordination”
  - spatial layout of graph nodes

[Davidson, Wylie, and Boyack. Cluster Stability and the Use of Noise in Interpretation of Clustering. Proc InfoVis 2001.]

Approach



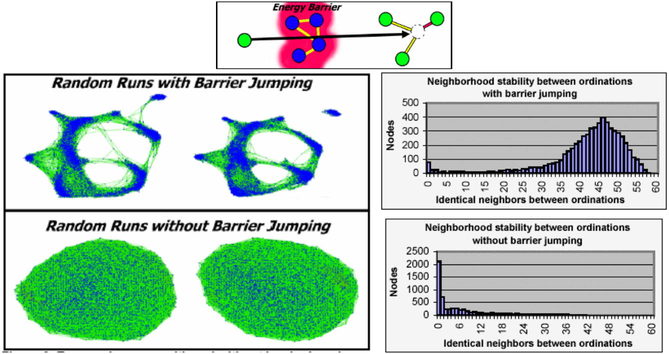
- normalize within each column
- similarity metric
  - discussion: Pearson's correllation coefficient
- threshold value for marking as similar
  - discussion: finding critical value

Graph Layout

- criteria
  - geometric distance matching graph-theoretic distance
    - vertices one hop away close
    - vertices many hops away far
  - insensitive to random starting positions
    - major problem with previous work!
  - tractable computation
- force-directed placement
  - discussion: energy minimization
  - others: gradient descent, etc
  - discussion: termination criteria

Barrier Jumping

- same idea as simulated annealing
  - but compute directly
  - just ignore repulsion for fraction of vertices
- solves start position sensitivity problem

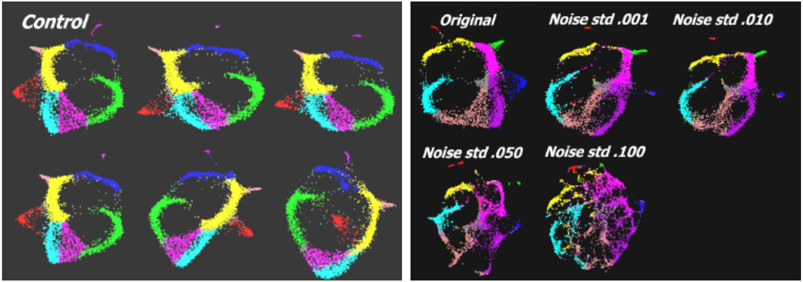


[Davidson, Wylie, and Boyack. Cluster Stability and the Use of Noise in Interpretation of Clustering. Proc InfoVis 2001.]

Results

- efficiency
  - naive approach: $O(V^2)$
  - approximate density field: $O(V)$
- good stability
  - rotation/reflection can occur

different random start adding noise



[Davidson, Wylie, and Boyack. Cluster Stability and the Use of Noise in Interpretation of Clustering. Proc InfoVis 2001.]

Critique

- real data
  - suggest check against subsequent publication!
- give criteria, then discuss why solution fits
- visual + numerical results
  - convincing images plus benchmark graphs
- detailed discussion of alternatives at each stage
- specific prescriptive advice in conclusion

HiDim: Readings

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

Fast Multidimensional Scaling through Sampling, Springs and Interpolation. Alistair Morrison, Greg Ross, Matthew Chalmers, Information Visualization 2(1) March 2003, pp. 68-77.

Visualizing the non-visual: spatial analysis and interaction with information from text documents. James A. Wise et al, Proc. InfoVis 1995

Hierarchical Parallel Coordinates for Visualizing Large Multivariate Data Sets Ying-Huey Fua, Matthew O. Ward, and Elke A. Rundensteiner, IEEE Visualization '99.

Cluster Stability and the Use of Noise in Interpretation of Clustering. George S. Davidson, Brian N. Wylie, Kevin W. Boyack, Proc InfoVis 2001.

HiDim: Further Reading

The Automated Multidimensional Detective. Alfred Inselberg and Tova Avidan. Proc. InfoVis 99, p 112-119

Visualizing Proximity Data. Rich DeJordy, Stephen P. Borgatti, Chris Roussin and Daniel S. Halgin. Field Methods, 19(3):239-263, 2007.

Interactive Hierarchical Dimension Ordering, Spacing and Filtering for Exploration Of High Dimensional Datasets. Jing Yang, Wei Peng, Matthew O. Ward and Elke A. Rundensteiner. Proc. InfoVis 2003.

A Data-Driven Reflectance Model. W Matusik, H. Pfister M. Brand and L. McMillan, Proc SIGGRAPH 2003, graphics.lcs.mit.edu/~wojciech/pubs/sig2003.pdf]

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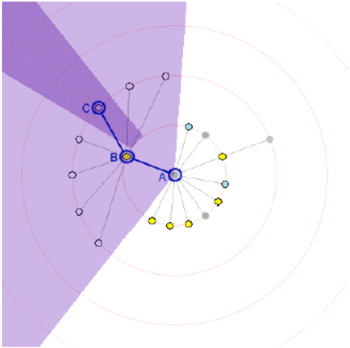
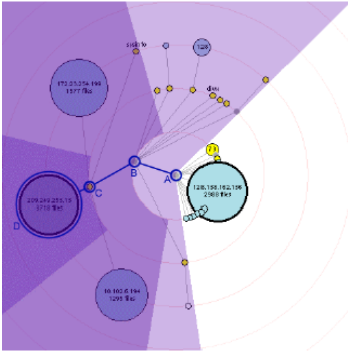
Animated Radial Layouts

- from static to dynamic radial layout (video)

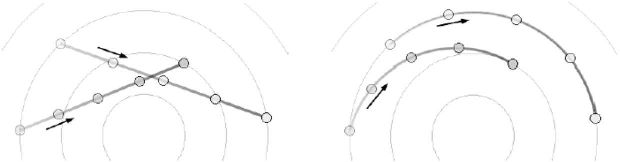




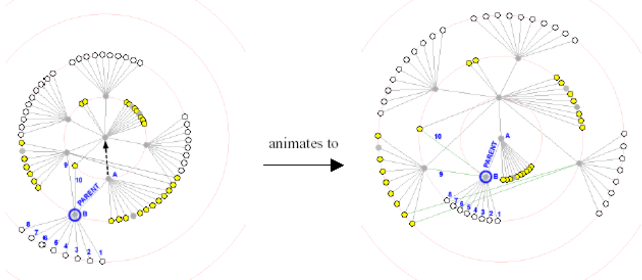
[Animated Exploration of Graphs with Radial Layout. Ka-Ping Yee, Danyel Fisher, Rachna Dhamija, and Marti Hearst, Proc InfoVis 2001. http://bailando.sims.berkeley.edu/papers/infovis01.htm]

Animation

- polar interpolation



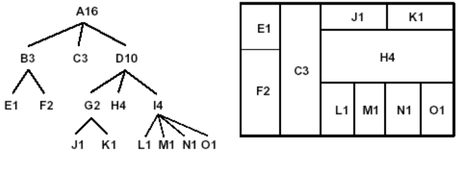
- maintain neighbor order (note prefuse bug!)



[Animated Exploration of Graphs with Radial Layout. Ka-Ping Yee, Danyel Fisher, Rachna Dhamija, and Marti Hearst, Proc InfoVis 2001.]

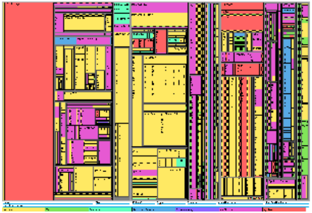
Treemaps

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

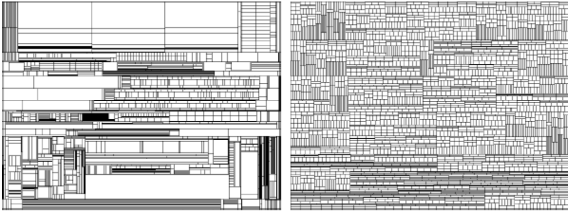


Node and link diagram

Treemap

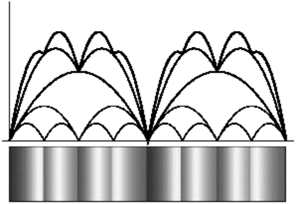
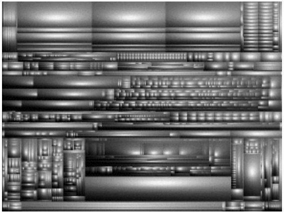
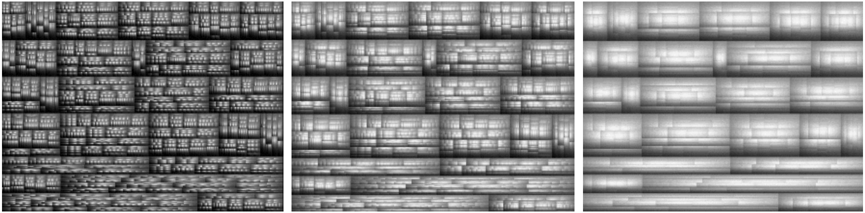


- difficulties reading



Cushion Treemaps

- show structure with shading
  - scale parameter controls global vs. local

[van Wijk and van de Wetering. Cushion Treemaps. Proc InfoVis 1999, pp 73-78. http://www.win.tue.nl/~vanwijk/ctm.pdf]

Critique

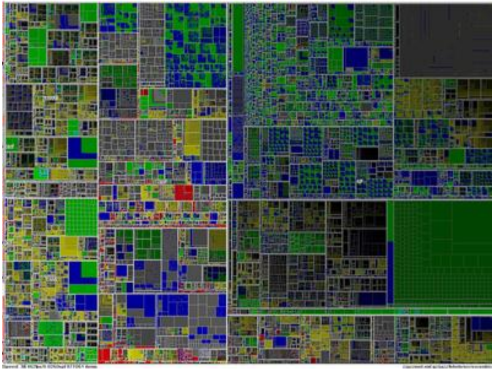
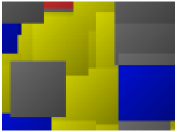
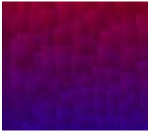
- good: use shading to free color for other encodings
- good: cushions do help show more internal hierarchical structure
- limitations: fundamental strength is unchanged
  - still best when focus is node attributes not topological structure

Treemap Applications

- cushion treemaps
  - SequoiaView, Windows app
  - hard drive usage
  - http://www.win.tue.nl/sequoiaview/
- one of the infovis tech-transfer success stories
  - http://www.cs.umd.edu/hcil/treemap-history/

Scaling Up Treemaps: MillionVis

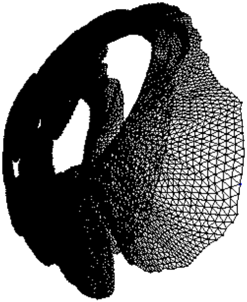
- shading not outline to visually distinguish with less pixels
- more GPU tricks, animation for transitions

[Interactive Information Visualization of a Million Items. Jean-Daniel Fekete and Catherine Plaisant, Proc InfoVis 2002.]

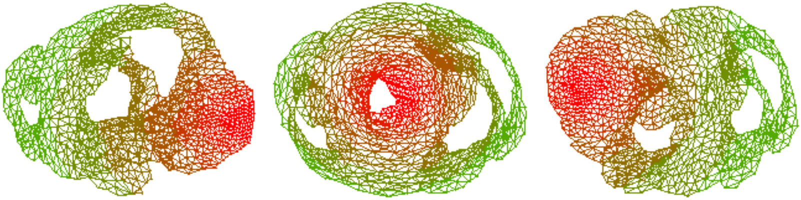
Topological Fisheye Views

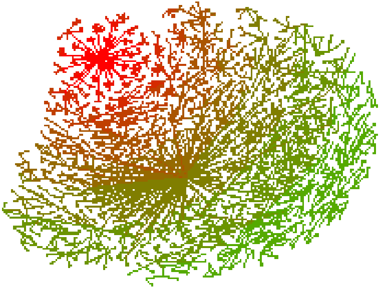
- input is laid-out graph
- preprocess: construct multilevel hierarchy by coarsening graphs
- user interactively controls focus point
- show hybrids made from several levels



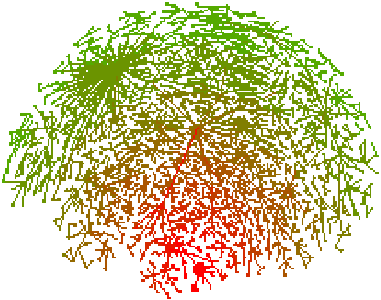
[Topological Fisheye Views for Visualizing Large Graphs. Gansner, Koren and North, IEEE TVCG 11(4), p 457-468, 2005.]

Topological Fisheye Views





focus on a top-left portion

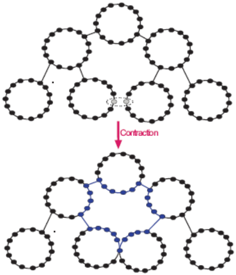


focus on a bottom portion

[Topological Fisheye Views for Visualizing Large Graphs. Gansner, Koren and North, IEEE TVCG 11(4), p 457-468, 2005.]

Coarsening Strategy

- must preserve graph-theoretic properties
  - topological distance (hops away), cycles
  - cannot just use geometric proximity alone
  - cannot just contract nodes/edges
  - exploit geometric information with proximity graph



[Topological Fisheye Views for Visualizing Large Graphs. Gansner, Koren and North, IEEE TVCG 11(4), p 457-468, 2005.]

Coarsening Requirements

- uniform cluster/metanode size
- match coarse and fine layout geometries
- scalable

4394-node approximation

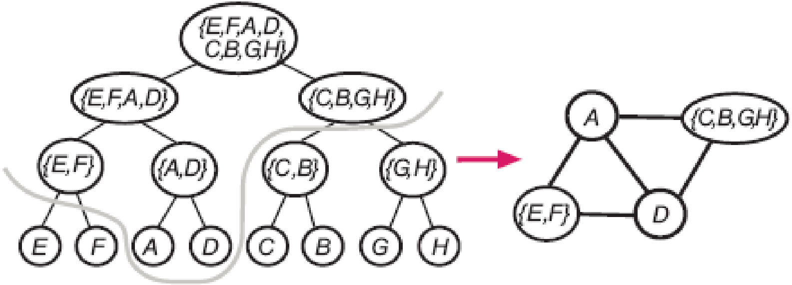
1223-node approximation

341-node approximation

[Topological Fisheye Views for Visualizing Large Graphs. Gansner, Koren and North, IEEE TVCG 11(4), p 457-468, 2005.]

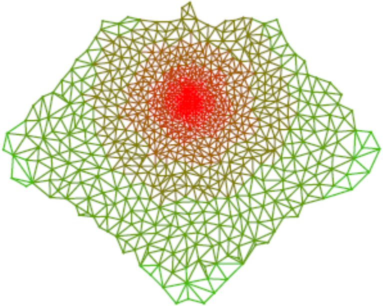
Hybrid Graph

- find active nodes

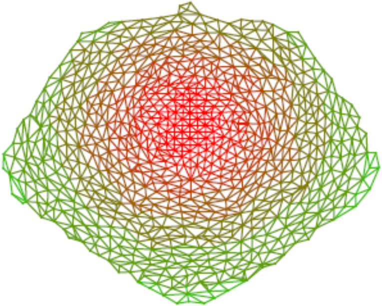


[Topological Fisheye Views for Visualizing Large Graphs. Gansner, Koren and North, IEEE TVCG 11(4), p 457-468, 2005.]

Distort For Uniform Density



(b) default layout of hybrid graph



(c) distorted layout of hybrid graph

[Topological Fisheye Views for Visualizing Large Graphs. Gansner, Koren and North, IEEE TVCG 11(4), p 457-468, 2005.]

Critique

- topologically sophisticated, not just geometric distortion
- rigorous approach

Graphs: Readings

Graph Visualisation in Information Visualisation: a Survey. Ivan Herman, Guy Melancon, M. Scott Marshall. IEEE Transactions on Visualization and Computer Graphics, 6(1), pp. 24-44, 2000. http://citeseer.nj.nec.com/herman00graph.html

Animated Exploration of Graphs with Radial Layout. Ka-Ping Yee, Danyel Fisher, Rachna Dhamija, and Marti Hearst, Proc InfoVis 2001. http://bailando.sims.berkeley.edu/papers/infovis01.htm

Cushion Treemaps. Jack J. van Wijk and Huub van de Wetering, Proc InfoVis 1999, pp 73-78. http://www.win.tue.nl/∼vanwijk/ctm.pdf

Interactive Information Visualization of a Million Items Jean-Daniel Fekete and Catherine Plaisant, Proc InfoVis 2002. [http://www.cs.umd.edu/local-cgi-bin/hcil/rr.pl?number=2002-01]

Topological Fisheye Views for Visualizing Large Graphs. Emden Gansner, Yehuda Koren and Stephen North, IEEE TVCG 11(4), p 457-468, 2005. http://www.research.att.com/areas/visualization/papers_videos/pdf/DBLP-conf-infovis-GansnerKN04.pdf

Graphs: Further Readings

IPSep-CoLa: An Incremental Procedure for Separation Constraint Layout of Graphs. Tim Dwyer, Kim Marriott, and Yehuda Koren. IEEE TVCG 12(5):821–828 (Proc. InfoVis 06), 2006.
http://www.research.att.com/∼yehuda/pubs/dwyer.pdf

Multiscale Visualization of Small World Networks. David Auber, Yves Chiricota, Fabien Jourdan, Guy Melancon, Proc. InfoVis 2003.
http://dept-info.labri.fr/∼auber/documents/publi/auberIV03Seattle.pdf

Online Dynamic Graph Drawing. Yaniv Frishman and Ayellet Tal. Proc EuroVis 2007, p 75-82.
http://www.ee.technion.ac.il/ ayellet/Ps/OnlineGD.pdf

TopoLayout: Multi-Level Graph Layout by Topological Features. Daniel Archambault, Tamara Munzner, and David Auber. IEEE TVCG 13(2):305–317, Mar/Apr 2007.

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

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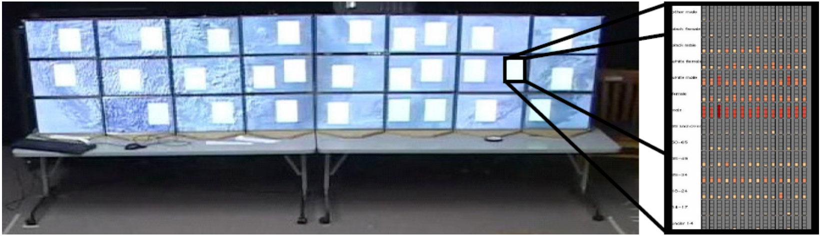
Perceptual Scalability

- what are perceptual/cognitive limits when screen-space constraints lifted?
  - 2 vs. 32 Mpixel display
  - macro/micro views
- perceptually scalable
  - no increase in task completion times when normalize to amount of data

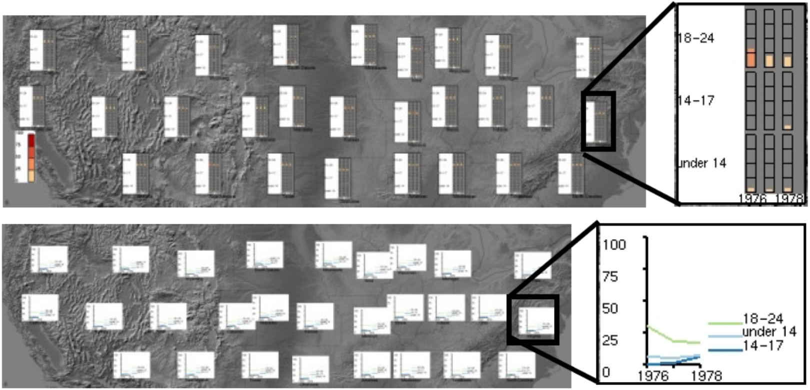


[The Perceptual Scalability of Visualization. Beth Yost and Chris North. IEEE TVCG 12(5) (Proc. InfoVis 06), Sep 2006, p 837-844.]

Perceptual Scalability

- design
  - 2 display sizes, between-subjects
    - (data size also increased proportionally)
  - 3 visualization designs, within
    - small multiples: bars
    - embedded graphs
    - embedded bars
  - 7 tasks, within
  - 42 tasks per participant
    - 3 vis x 7 tasks x 2 trials

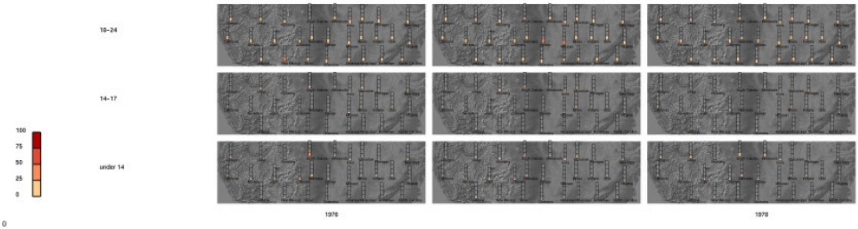
Embedded Visualizations



[The Perceptual Scalability of Visualization. Beth Yost and Chris North. IEEE TVCG 12(5) (Proc. InfoVis 06), Sep 2006, p 837-844.]

Small Multiples Visualizations

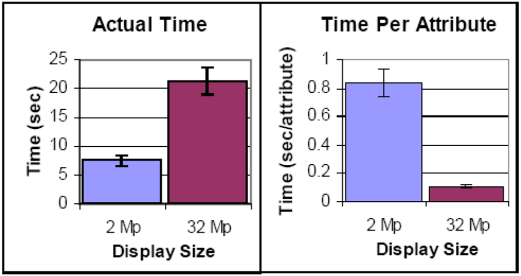
- attribute-centric instead of space-centric



[The Perceptual Scalability of Visualization. Beth Yost and Chris North. IEEE TVCG 12(5) (Proc. InfoVis 06), Sep 2006, p 837-844.]

Results

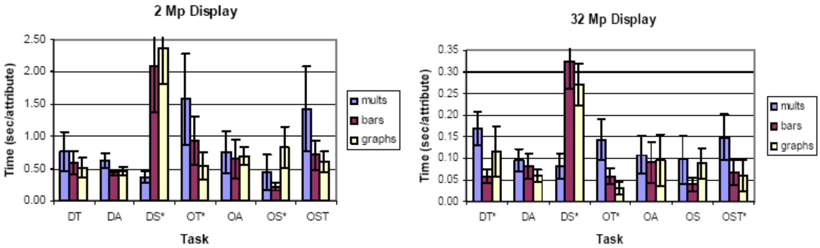
- 20x increase in data, but only 3x increase in absolute task times



[The Perceptual Scalability of Visualization. Beth Yost and Chris North. IEEE TVCG 12(5) (Proc. InfoVis 06), Sep 2006, p 837-844.]

Results

- significant 3-way interaction
  - between display, size, task



[The Perceptual Scalability of Visualization. Beth Yost and Chris North. IEEE TVCG 12(5) (Proc. InfoVis 06), Sep 2006, p 837-844.]

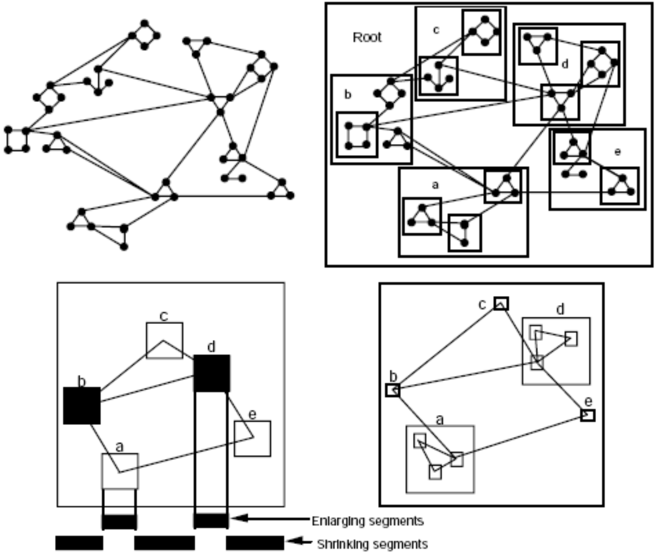
Results

- visual encoding important on small displays
  - DS: mults sig slower than graphs on small
  - DS: mults sig slower than embedded on large
  - OS: bars sig faster than graphs for small
  - OS: no sig difference bars/graphs for large
- spatial grouping important on large displays
  - embedded sig faster+preferred over small mult
  - no bar/graph differences

Critique

- first study of macro/micro effects
  - breaking new ground
- many possible followups
  - physical navigation vs. virtual navigation

Fisheye Multilevel Networks



[Navigating Hierarchically Clustered Networks through Fisheye and Full-Zoom Methods. Schaffer et al. ACM ToCHI 3(2) p 162-188, 1996.]

Lab Experiment

- 2 interfaces (fisheye, zoom)
- 2 tasks (isomorphic)
  - stages: find and repair
- within subjects, counterbalanced order
- 20 participants
- data: 154 nodes, 39 clusters
- measurements
  - completion time
  - number of zooms
  - success

Results

- sig effect of interface: fisheye faster
- but no differences with find subtask
  - information visible in both displays
- solution quality differed: fisheye better
  - local rerouting difficult in full-zoom

Field Experiment

- 2 real control room operators
- response times similar
  - no statistical analysis, too few subjects
- expressed preference for fisheye over full-zoom
  - (experimenter effect?)
- concerns about fisheye: missing details

Critique

- nicely designed study
- useful discussion of qualitative observations
- very good to do field followup with real operators

Pictures Into Numbers

- field study
- participants: professional meterologists
  - two people: forecaster, technician
- interfaces: multiple programs used
- protocol
  - talkaloud
  - videotaped sessions with 3 cameras

[Turning Pictures into Numbers: Extracting and Generating Information from Complex Visualizations. Trafton et al. Intl J. Human Computer Studies 53(5), 827-850.]

Cognitive Task Analysis

- initialize understanding of large scale weather
- build qualitative mental model (QMM)
- verify and adjust QMM
- write the brief

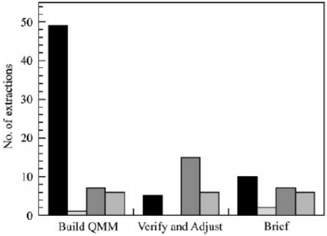
- task breakdown part of paper contribution

Coding Methodology

- interface
  - which interface used
  - whether picture/chart/graph
- usage (every utterance!)
  - goal
  - extract
    - quant/qual
    - goal-oriented/opportunistic
    - integrated/unintegrated
  - brief-writing
    - quant/qual
    - QMM/vis/notes

Results

- sig difference between vis used at CTA stages
  - charts to build QMM
  - images to verify/adjust QMM
  - all kinds during brief-writing
- many others...



The relation between the stage of the CTA and the type of visualization used by the forecasters: ■, chart; ■, graph; ■, picture; ■, text.

[Turning Pictures into Numbers: Extracting and Generating Information from Complex Visualizations. Trafton et al. Intl J. Human Computer Studies 53(5), 827-850.]

Critique

- video coding is huge amount of work, but very illuminating
  - untangling complex story of real tool use
- methodology of CTA construction not discussed here
  - often bottomup/topdown mix

Studies: Readings

The Perceptual Scalability of Visualization. Beth Yost and Chris North. Proc. InfoVis 06, published as IEEE TVCG 12(5), Sep 2006, p 837-844.

Navigating Hierarchically Clustered Networks through Fisheye and Full-Zoom Methods. Doug Schaffer, Zhengping Zuo, Saul Greenberg, Lyn Bartram, John C. Dill, Shelli Dubs, and Mark Roseman. ACM Trans. Computer-Human Interaction (ToCHI), 3(2) p 162-188, 1996.

Turning Pictures into Numbers: Extracting and Generating Information from Complex Visualizations. J. Gregory Trafton, Susan S. Kirschenbaum, Ted L. Tsui, Robert T. Miyamoto, James A. Ballas, and Paula D. Raymond. Intl Journ. Human Computer Studies 53(5), 827-850.

Further Readings

Task-Centered User Interface Design, Clayton Lewis and John Rieman, Chapters 0-5.

The challenge of information visualization evaluation Catherine Plaisant. Proc. Advanced Visual Interfaces (AVI) 2004

Information Visualization: Perception for Design. Appendix C: The Perceptual Evaluation of Visualization Techniques and Systems. Colin Ware. Morgan Kaufmann, 2000.

Snap-Together Visualization: Can Users Construct and Operate Coordinated Views? Chris North, B. Shneiderman. Intl. Journal of Human-Computer Studies, Academic Press, 53(5), pg. 715-739, (November 2000).