Introduction to Visualization part 2

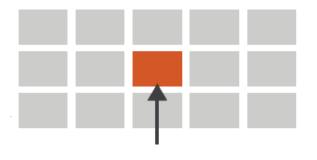
Noeska Smith, Jan Byška et al., UiB Dept. of Informatics, 2017-08-28



Various Types of Data



table data



spatial data



network data

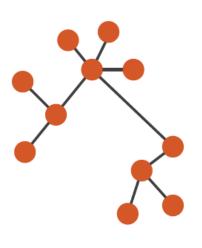


Table Data

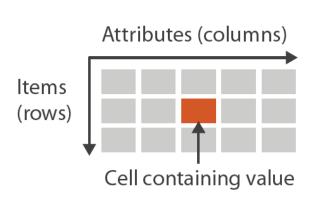


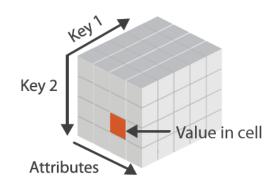
key

- unique independent attribute
 - row index

values

- dependent attribute, value of a cell
- quantitative vs. categorical
 - animal weight vs. animal species





Scatterplot



no keys, only values

2 quantitative attributes

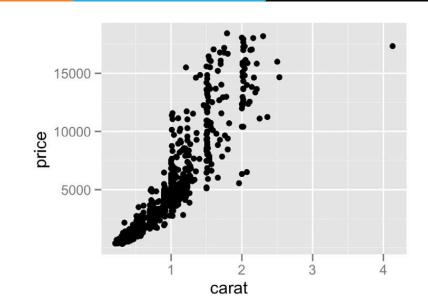
mark: points

channels

horizontal + vertical position

tasks

 find trends, outliers, distribution, correlation, clusters



A layered grammar of graphics. Wickham. J. Comp. Graph. Stat., 2010.

scalability

hundreds of items

Bar Chart



one key, one value

1 categorical attribute, 1 quantitative attribute

mark: lines

channels

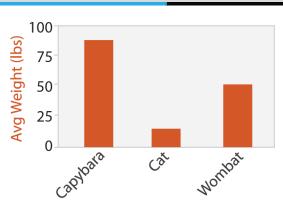
- length to express quantitative values
- spatial regions: one per mark
 - ordered by label (alphabetical),
 - ordered by length attribute (data-driven)

task

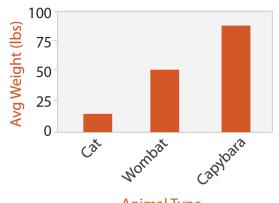
compare, lookup values

scalability

dozens to hundreds of levels for key attribute



Animal Type



Animal Type

Line Chart / Dot Plot

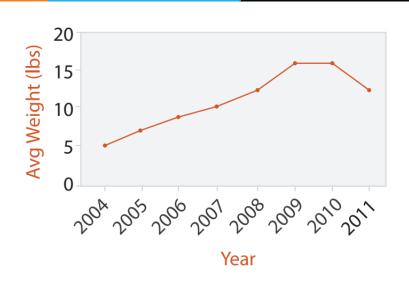


one key, one value

2 quantitative attributes

mark: points

- plus line connection marks
 - explicitly showing relationship between items



channels

- length (position) to express quantitative values
- separated and ordered by key attribute

task

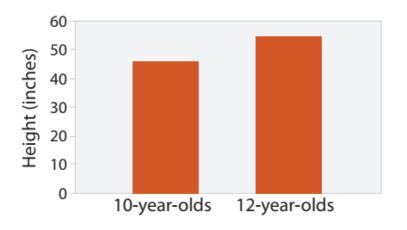
find trend

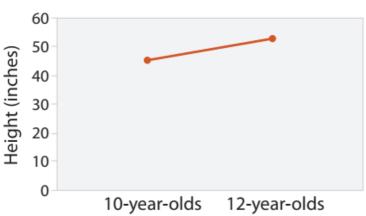
Choosing Bar or Line Chart



depends on type of key attribute

- bar charts if categorical
- line charts if ordered (quantitative)



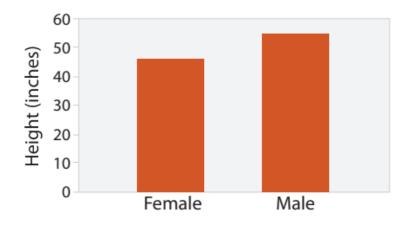


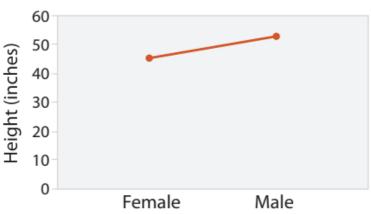
Choosing Bar or Line Chart



do not use line charts for categorical key attributes

- implication of trend so strong that it overrides semantics!
 - "The more male a person is, the taller he/she is."





Stacked Bar Chart



data: 2 categorical attributes, 1 quantitative attribute

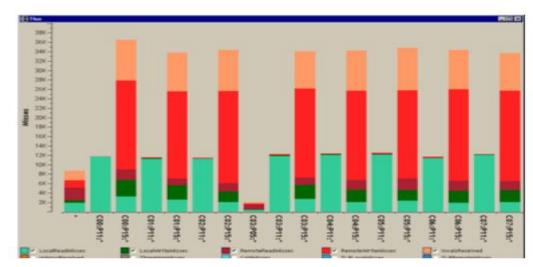
mark: vertical stack of line marks

channels

- length
- color hue
- spatial regions
 - one per stacked bar

task

part-to-whole relationship



Using Visualization to Understand the Behavior of Computer Systems. Bosch. Ph.D. thesis, Stanford Computer Science, 2001.

scalability

several to one dozen levels for stacked attribute

Streamgraph



generalized stacked graph

emphasizing horizontal continuity vs. vertical items

data

- 1 categorical key attribute (artist)
- 1 ordered key attribute (time)
- 1 quantitative value attribute (counts)

derived data

- geometry: layers -> height encodes counts
- 1 quantitative attribute (layer ordering)

Stacked Graphs Geometry & Aesthetics. Byron and Wattenberg. IEEE TVCG, 2008.

scalability

- hundreds of time keys
- dozens to hundreds of artist keys
 - more than stacked bars, since most layers don't extend across whole chart

Heatmap



two keys, one value

- 2 categorical attributes (gene, experimental condition)
- 1 quantitative attributes (expression levels)

marks: area

- separate and align in 2D matrix
 - indexed (ordered) by 2 categorical attributes

channels

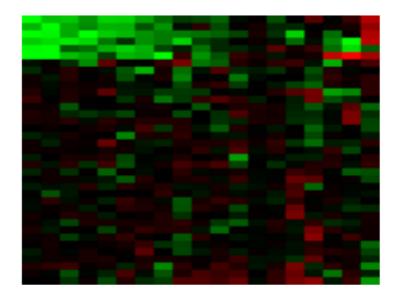
- color by quantitative attribute
 - ordered vs. diverging color map

task

find clusters, outliers

scalability

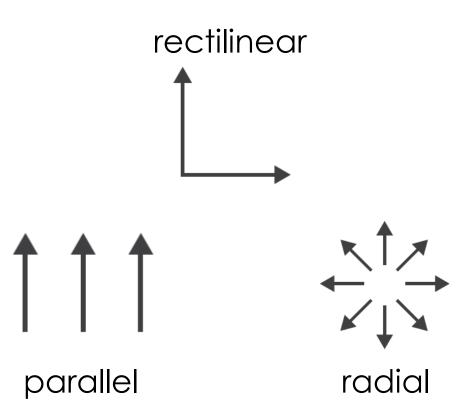
1K categorical levels, 1M items; only ~10 quantitative attribute levels



Multiple Axis



Math	Physics	Dance	Drama
85	95	70	65
90	80	60	50
65	50	90	90
50	40	95	80
40	60	80	90



Scatterplot Matrix

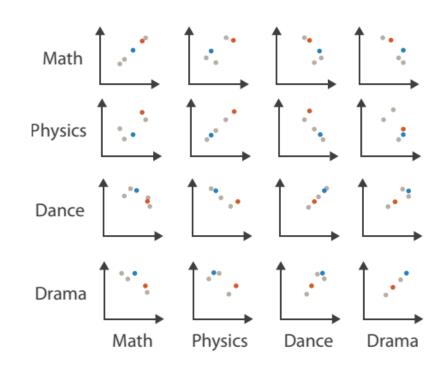


rectilinear axes, point mark

all possible pairs of axes

scalability

- one dozen attributes
- dozens to hundreds of items



Parallel Coordinates

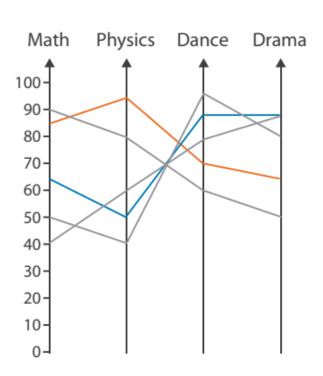


parallel axes, jagged line representing item

- parallel axes, item as point
 - axis ordering is major challenge

scalability

- dozens of attributes
- hundreds of items



Task: Correlation

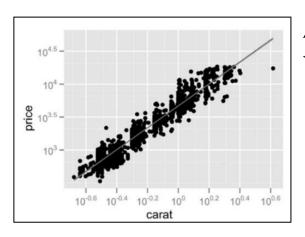


scatterplot matrix

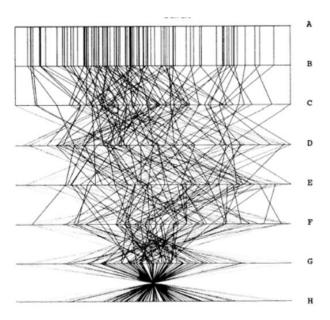
- positive correlation
 - diagonal low-to-high
- negative correlation
 - diagonal high-to-low
- uncorrelated
 - scattered points

parallel coordinates

- positive correlation
 - parallel line segments
- negative correlation
 - all segments cross at halfway point
- uncorrelated
 - scattered crossings



A layered grammar of graphics. Wickham. J. Comp. Graph. Stat. 19:1, 2010.



Hyper dimensional Data Analysis Using Parallel Coordinates. Wegman. JASA, 1990.

Pie chart, Polar Area Chart



data

- 1 categorical key attribute
- 1 quantitative value attribute

pie chart

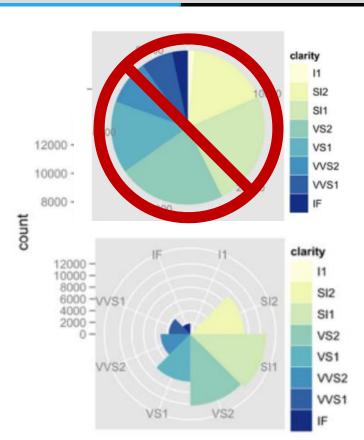
- area marks with angle channel
- accuracy: angle/area much less accurate

polar area chart

- area marks with length channel
- more direct analog to bar charts

task

part-to-whole judgements



Orientation Limitations



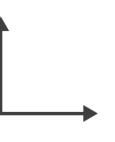
rectilinear: scalability w.r.t. #axes

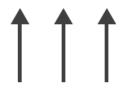
- 2 axes best
- 3 problematic
- 4+ impossible

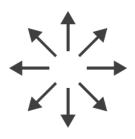
parallel: unfamiliarity, training time

radial: perceptual limits

- angles lower precision than lengths
- asymmetry between angle and length







Spatial Data



geometry

geographical, other derived

spatial fields (one value per cell)

- scalar fields (one value per cell)
 - iso-contours
 - direct volume rendering
- vector and tensor fields (many values per cell)
 - flow glyphs (local)
 - geometric (sparse seeds)
 - textures (dense seeds)
 - features (globally derived)



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Choropleth Map



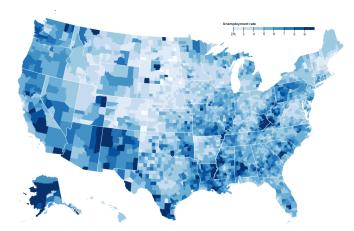
table with 1 quantitative attribute per region

encoding

- geometry for area mark boundaries
- sequentially segmented color map

task

understanding spatial relationships



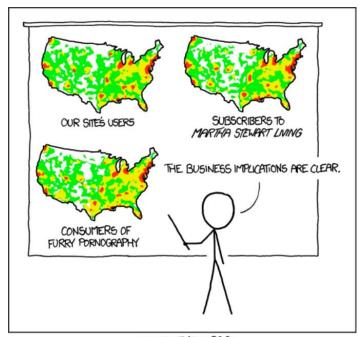
Beware: Population Maps Trickiness!



consider when to normalize by population density

general issue

- absolute counts
- relative/normalized data



PET PEEVE #208: GEOGRAPHIC PROFILE MAPS WHICH ARE BASICALLY JUST POPULATION MAPS

Topographic Map



1 quantitative attribute per 2D grid cell

- geographic geometry
- scalar spatial field

task

 shape understanding, spatial relationships

derived data

 isocontours computed for specific levels of scalar values



Land Information New Zealand Data Service

Isosurfaces, Direct Volume Rendering



1 quantitative attribute per 3D grid cell

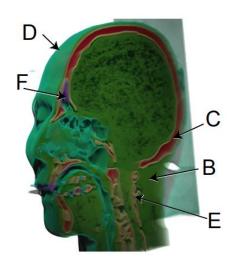
scalar spatial field

task

shape understanding, spatial relationships

derived data

isocontours computed for specific levels of scalar values



Multidimensional Transfer Functions for Volume Rendering. Kniss, Kindlmann, and Hansen. The Visualization Handbook, 2005.

direct volume rendering

transfer function maps scalar values to color, opacity

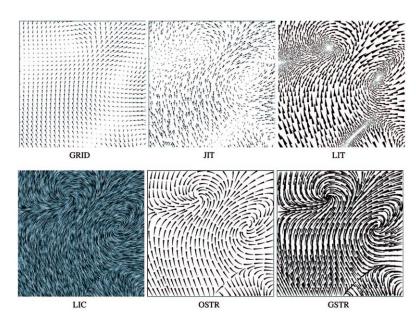
Vector and Tensor Fields



many attributes per cell

idiom families

- flow glyphs
 - purely local
- geometric flow
 - derived data from tracing particle trajectories
 - sparse set of seed points
- texture flow
 - derived data, dense seeds
- feature flow
 - global computation to detect features
 - encoded with one of methods above



Comparing 2D vector field visualization methods: A user study. Laidlaw et al. IEEE TVCG, 2005.

Streamlines



3D vector field

derived data (from field)

streamlines: trajectory particle will follow

derived data (per streamline)

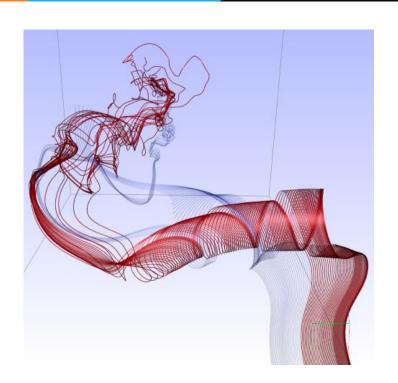
- curvature, torsion, tortuosity
- signature: complex weighted combination
- compute cluster hierarchy across all signatures
- encode: color and opacity by cluster

tasks

find features, query shape

scalability

millions of samples, hundreds of streamlines



Similarity Measures for Enhancing Interactive Streamline Seeding. McLoughlin,. Jones, Laramee, Malki, Masters, and. Hansen. IEEE TVSG, 2013

Network and Tree Data

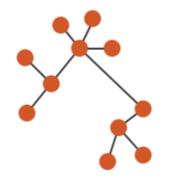


Node-Link Diagrams

Connection Marks







Adjacency Matrix

Derived Table







Force Directed Placement



visual encoding: node-link diagram

link connection marks, node point marks

algorithm: energy minimization

- analogy: nodes repel, links draw together like springs
- optimization problem: minimize crossings

spatial position: no meaning directly encoded

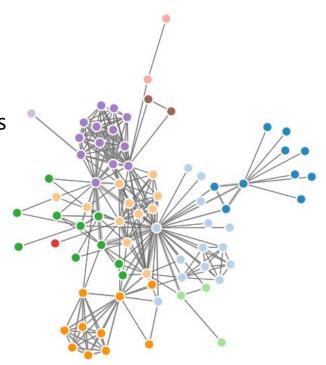
proximity can be meaningful or arbitrary

tasks

explore topology; locate paths, clusters

scalability

node/edge density E < 4N



Multilevel Force-Directed Placement

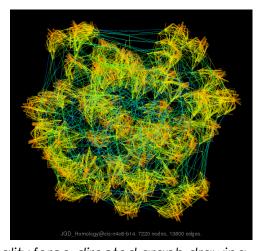


derived data: cluster hierarchy

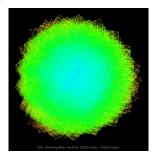
- better algorithm for same encoding technique
- same: fundamental use of space

scalability

- nodes, edges: 1K-10K
- hairball problem still hits eventually



Efficient and high quality force-directed graph drawing. Hu. The Mathematica Journal, 2005.



Adjacency Matrix View



data: network

transform into same data/encoding as heatmap

derived data: table from network

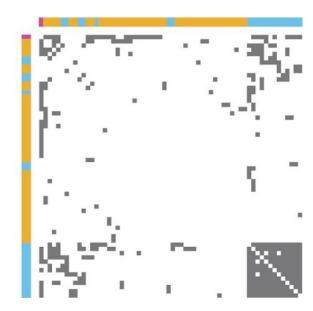
- 1 quantitative attribute
 - weighted edge between nodes
- 2 categorical attributes: node list x 2

visual encoding

cell shows presence/absence of edge

scalability

- 1K nodes, 1M edges



Points of view: Networks. Gehlenborg and Wong. Nature Methods, 2012

Connection vs. Adjacency Comparison



adjacency matrix strengths

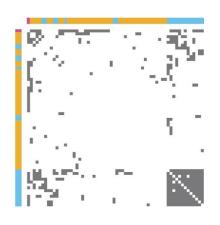
- predictability, scalability, supports reordering
- some topology tasks trainable

node-link diagram strengths

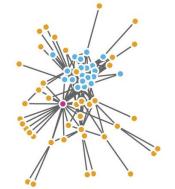
- topology understanding, path tracing
- intuitive, no training needed

empirical study

- node-link best for small networks
- matrix best for large networks
 - if tasks don't involve topological structure!



Points of view: Networks. Gehlenborg and Wong. Nature Methods, 2012



Radial Node-Link Tree



data: tree

encoding

- link connection marks
- point node marks
- radial axis orientation
 - angular proximity: siblings
 - distance from center: depth in tree

tasks

understanding topology, following paths

scalability

1K - 10K nodes



Treemap



data: tree

1 quantitative attribute at leaf nodes

encoding

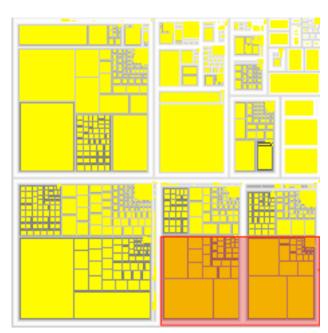
- area containment marks for hierarchical structure
- rectilinear orientation
- size encodes quantitative attribute

tasks

query attribute at leaf nodes

scalability

1M leaf nodes



Introduction to Visualization part 3

Noeska Smith, Jan Byška et al., UiB Dept. of Informatics, 2017-08-28

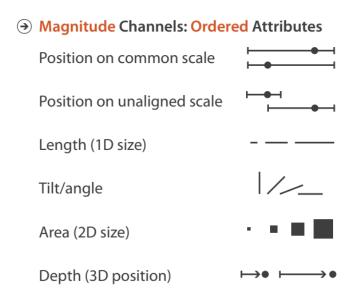


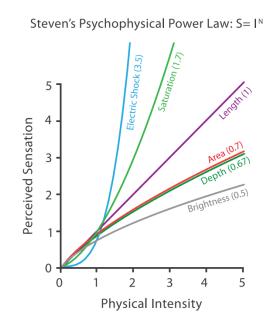
No Unjustified 3D: Power of the Plane



high-ranked spatial position channels:

– planar spatial position **not depth!**



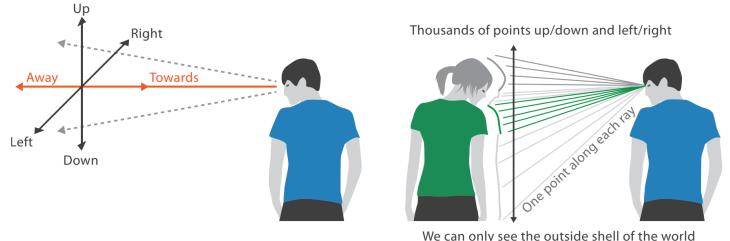


No Unjustified 3D: Power of the Plane



we don't really live in 3D: we see in 2.5D

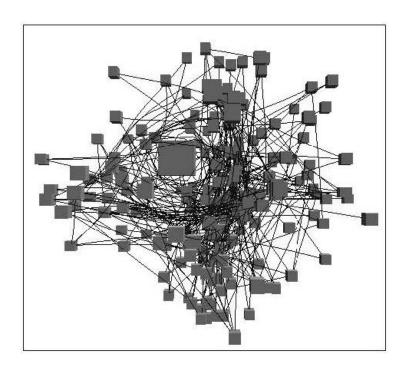
- acquire more info on image plane quickly from eye movements
- acquire more info for depth slower, from head/body motion



No Unjustified 3D: Occlusion



occlusion interaction complexity



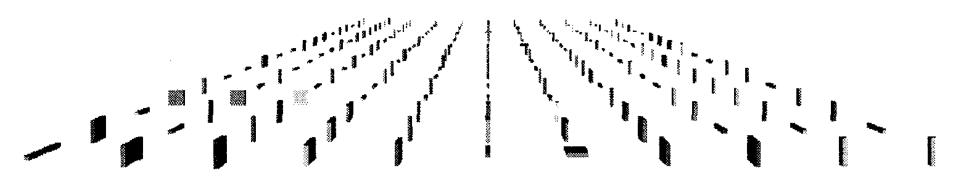
Distortion Viewing Techniques for 3D Data. Carpendale et al. InfoVis, 1996.

No Unjustified 3D: Distortion



perspective distortion

interferes with all size channel encodings

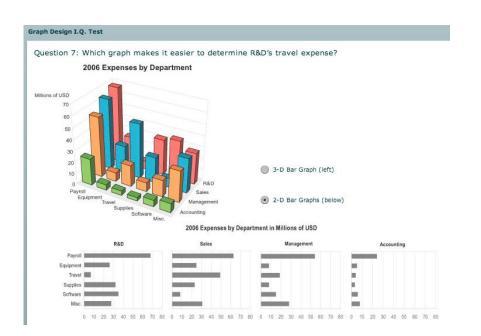


Visualizing the Results of Multimedia Web Search Engines. Mukherjea, Hirata, and Hara. InfoVis, 1996

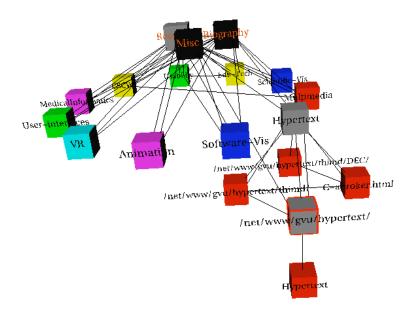
No Unjustified 3D: Examples



3D bars never a good idea!



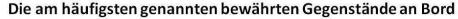
text legibility

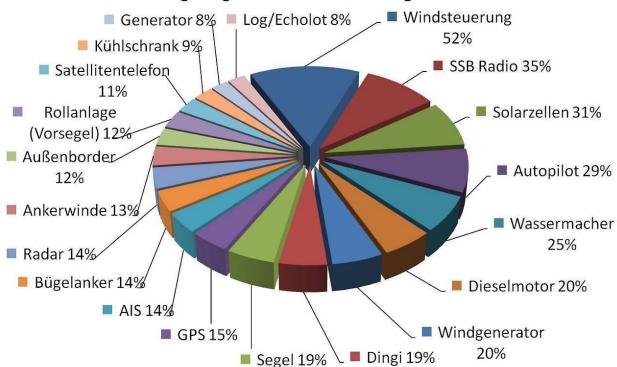


Visualizing the World-Wide Web with the Navigational View Builder. Mukherjea and Foley. Computer Networks and ISDN Systems, 1995.

No Unjustified 3D: Examples



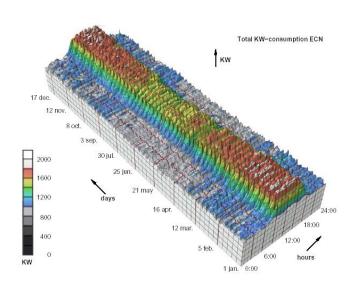


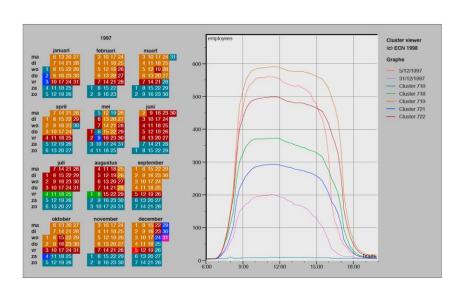


No Unjustified 3D: Examples



extruded curves: detailed comparisons impossible multiple views: calendar, superimposed 2D curves





Cluster and Calendar based Visualization of Time Series Data. van Wijk and van Selow, Proc. InfoVis, 1999.

Justified 3D: Shape Perception



benefits outweigh costs when task is shape perception for 3D spatial data

interactive navigation supports synthesis across many

viewpoints

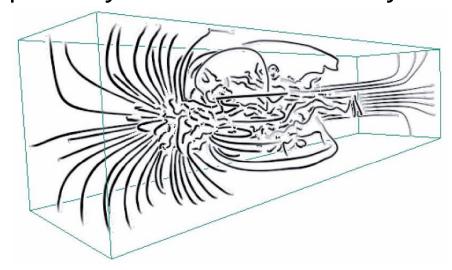


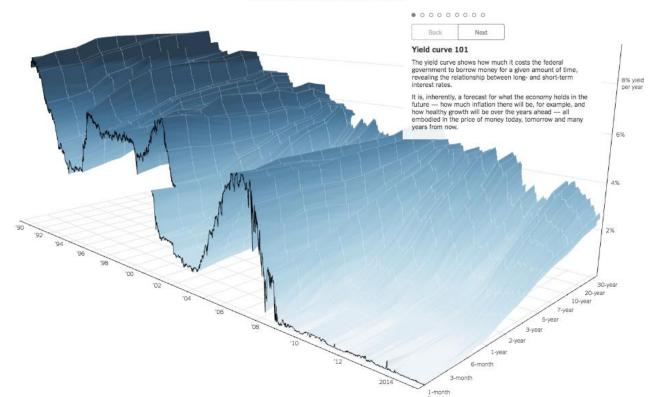
Image-Based Streamline Generation and Rendering. Li and Shen. IEEE TVCG, 2007.

Justified 3D: Economic Growth Curve



A 3-D View of a Chart That Predicts The Economic Future: The Yield Curve

By GREGOR AISCH and AMANDA COX MARCH 18, 2015

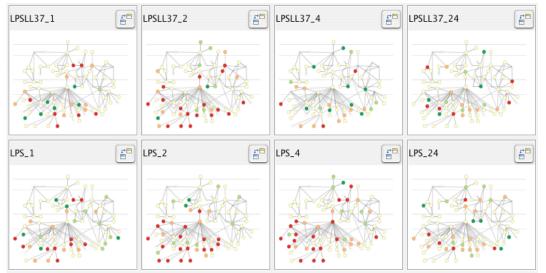


Eyes Beat Memory



small multiples: one graph instance per experimental condition can be better then animation

same spatial layout vs. color differently, by condition



Cerebral: Visualizing Multiple Experimental Conditions on a Graph with Biological Context. Barsky, Munzner, Gardy, and Kincaid. IEEE TVCG, 2008.

No Unjustified 2D



consider whether network data requires 2D spatial layout

- especially if reading text is central to task!
- arranging as network means lower information density and harder label lookup compared to text lists

benefits outweigh costs when topological structure/context important for task

 be especially careful for search results, document collections, ontologies

Final Words



overview first, zoom and filter, details on demand

mantra from Shneiderman

start with focus on functionality

straightforward to improve aesthetics later on, as refinement

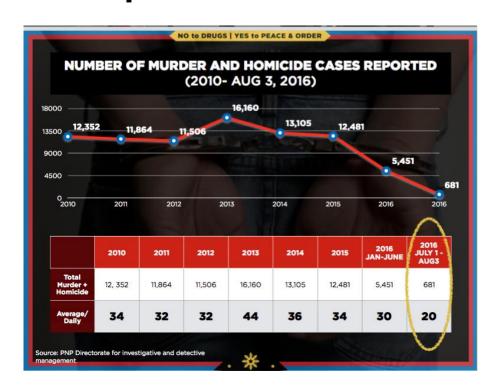
dangerous to start with aesthetics

usually impossible to add function retroactively

Beware!



Visualization can be exploited to confuse or to misinform!



Acknowledgement



the source for this talk

– http://www.cs.ubc.ca/~tmm/talks.html

book page (including tutorial lecture slides)

- http://www.cs.ubc.ca/~tmm/vadbook
- http://www.crcpress.com/product/isbn/9781466508910
- 20% promo code for book+ebook combo: HVN17

illustrations: Eamonn Maguirethe

