

Visualization Analysis & Design



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<http://www.cs.ubc.ca/~tmm/talks.html#vad21biomedvis>

Why is validation difficult?

- different ways to get it wrong at each level



<http://www.cs.ubc.ca/~tmm/talks.html#vad21biomedvis>

Visualization: definition & motivation

Computer-based visualization systems provide visual representations of datasets designed to help people carry out tasks more effectively.

Visualization is suitable when there is a need to augment human capabilities rather than replace people with computational decision-making methods.

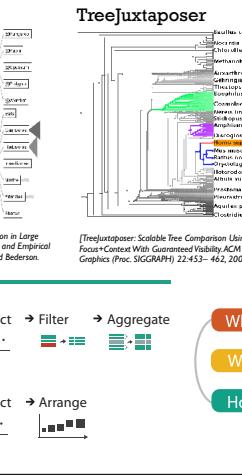
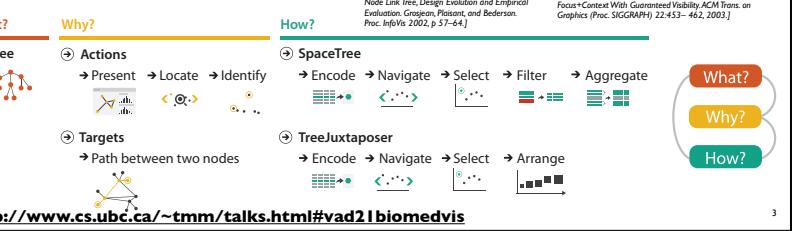
- human in the loop needs the details & no trusted automatic solution exists
 - doesn't know exactly what questions to ask in advance
 - exploratory data analysis
 - speed up** through human-in-the-loop visual data analysis
 - present known results to others
 - stepping stone towards automation
 - before model creation to provide understanding
 - during algorithm creation to refine, debug, set parameters
 - before or during deployment to build trust and monitor

more at:
Visualization Analysis and Design.
Munzner. CRC Press, 2014.

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Why analyze?

- imposes a structure on huge design space
- scaffold to help you think systematically about choices
- analyzing existing as stepping stone to designing new

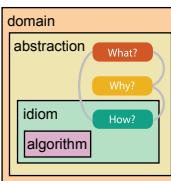


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Analysis framework: Four levels, three questions

- domain situation**
 - who are the target users?
- abstraction**
 - translate from specifics of domain to vocabulary of vis
- what** is shown? **data abstraction**
- why** is the user looking at it? **task abstraction**
- idiom**
 - how is it shown?
 - visual encoding idiom**: how to draw
 - interaction idiom**: how to manipulate
- algorithm**
 - efficient computation

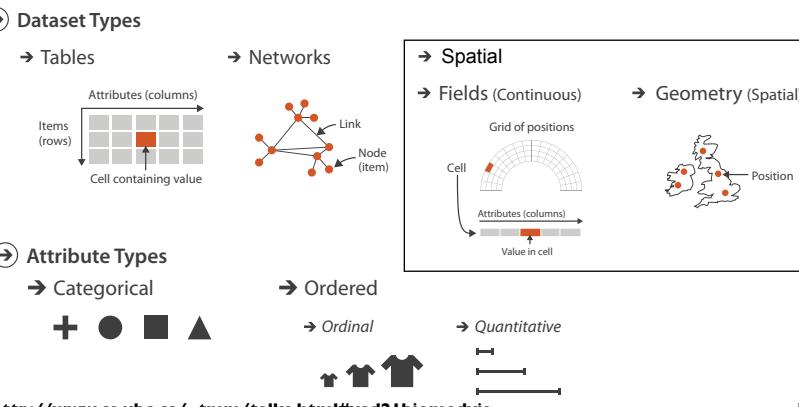
[A Nested Model of Visualization Design and Validation.
Munzner. IEEE TVCG 15(6):921-928, 2009 (Proc. InfoVis 2009).]



[A Multi-Level Typology of Abstract Visualization Tasks.
Brehmer and Munzner. IEEE TVCG 19(1):237-2385, 2013 (Proc. InfoVis 2013).]

<http://www.cs.ubc.ca/~tmm/talks.html#vad21biomedvis>

Types: Datasets and data



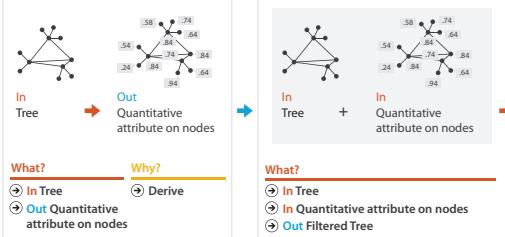
<http://www.cs.ubc.ca/~tmm/talks.html#vad21biomedvis>

Analysis example: Derive one attribute

- Strahler number
 - centrality metric for trees/networks
 - derived quantitative attribute
 - draw top 5K of 500K for good skeleton

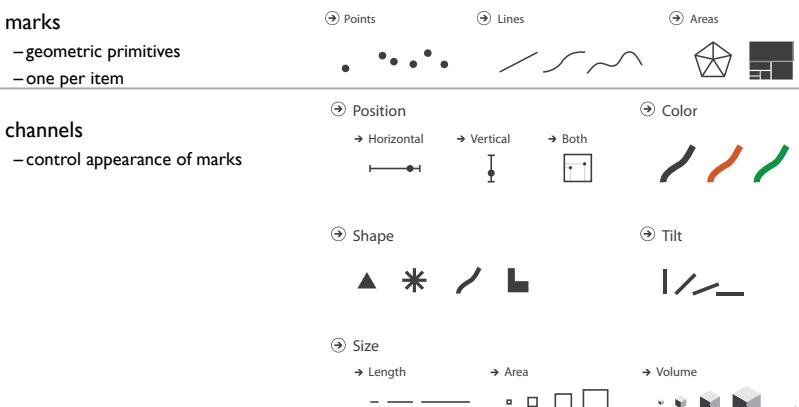


[Using Strahler numbers for real time visual exploration of huge graphs. Auber. Proc. Int'l. Conf. Computer Vision and Graphics, pp. 56-69, 2002.]



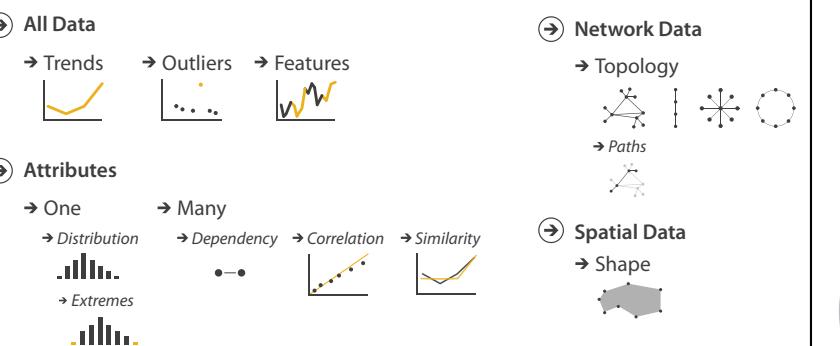
<http://www.cs.ubc.ca/~tmm/talks.html#vad21biomedvis>

Definitions: Marks and channels



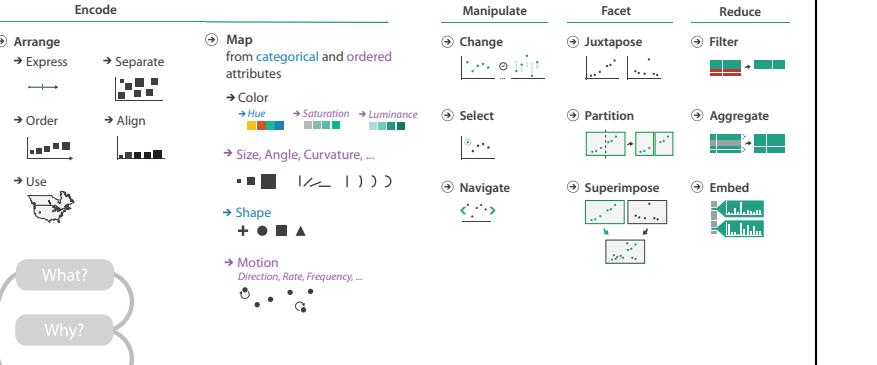
<http://www.cs.ubc.ca/~tmm/talks.html#vad21biomedvis>

Targets



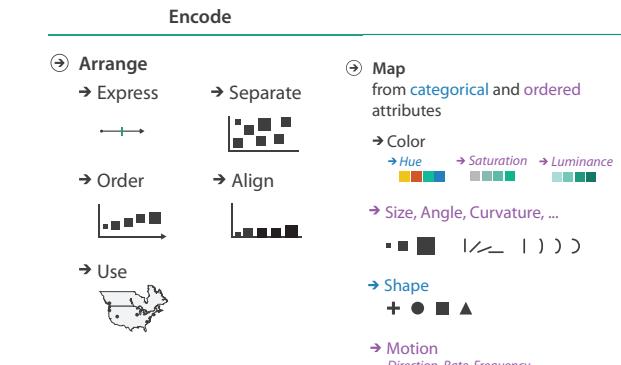
<http://www.cs.ubc.ca/~tmm/talks.html#vad21biomedvis>

How?



<http://www.cs.ubc.ca/~tmm/talks.html#vad21biomedvis>

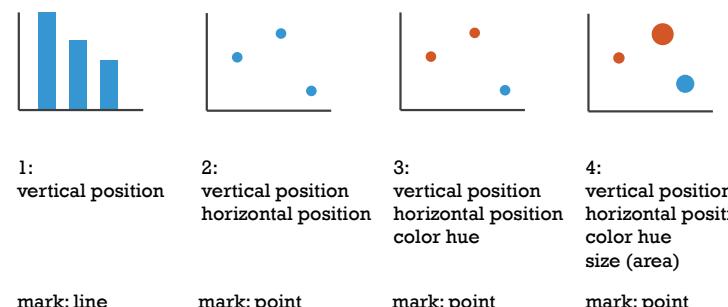
How to encode: Arrange space, map channels



<http://www.cs.ubc.ca/~tmm/talks.html#vad21biomedvis>

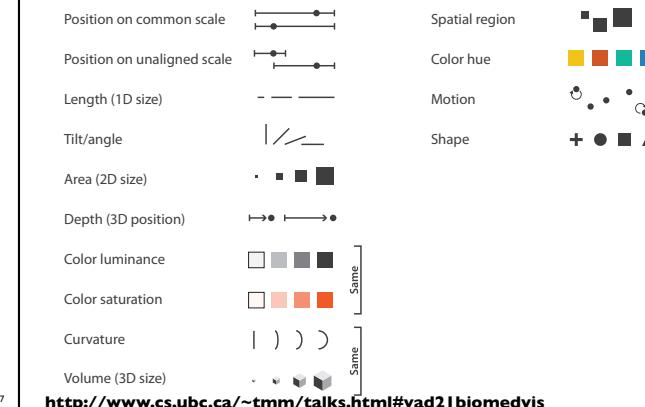
Encoding visually with marks and channels

- analyze idiom structure
- as combination of marks and channels



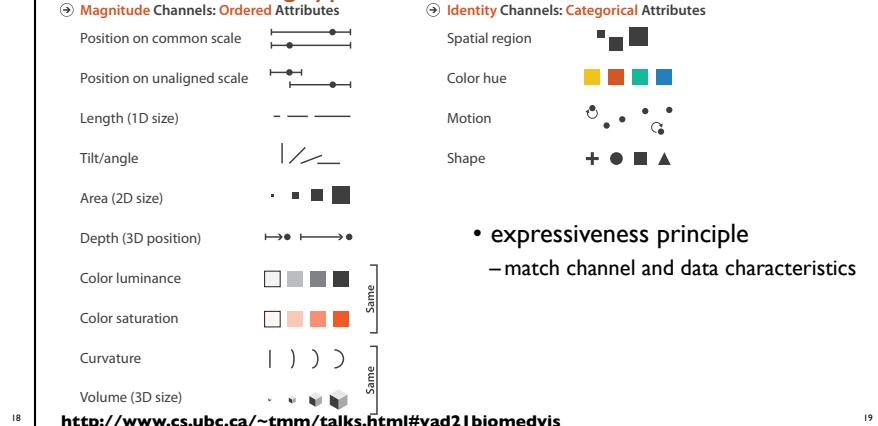
<http://www.cs.ubc.ca/~tmm/talks.html#vad21biomedvis>

Channels



<http://www.cs.ubc.ca/~tmm/talks.html#vad21biomedvis>

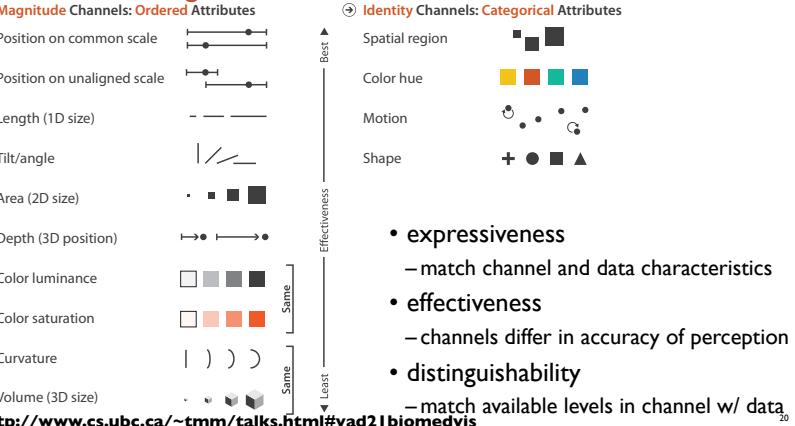
Channels: Matching Types



- expressiveness principle
- match channel and data characteristics

<http://www.cs.ubc.ca/~tmm/talks.html#vad21biomedvis>

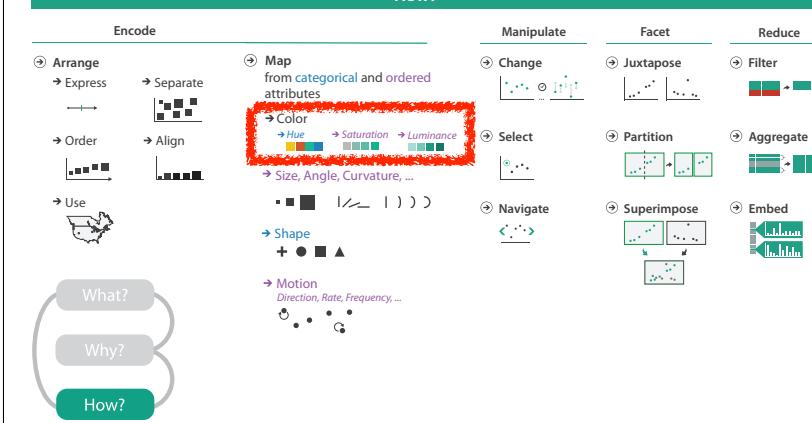
Channels: Rankings



- expressiveness
- match channel and data characteristics
- effectiveness
- channels differ in accuracy of perception
- distinguishability
- match available levels in channel w/ data

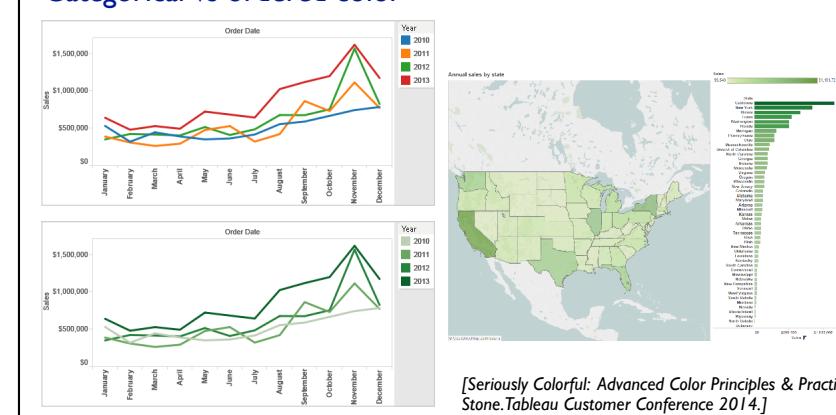
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How?



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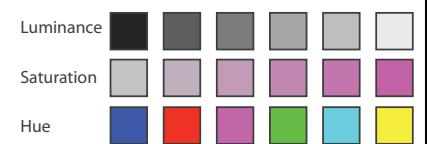
Categorical vs ordered color



<http://www.cs.ubc.ca/~tmm/talks.html#vad21biomedvis>

Decomposing color

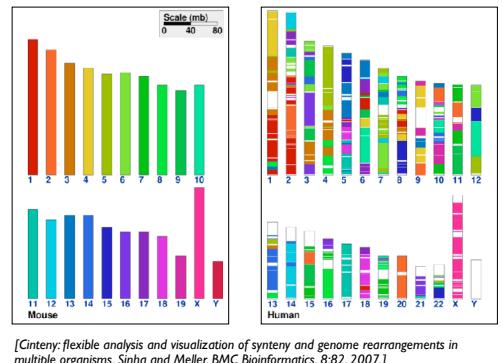
- first rule of color: do not talk about color!
- color is confusing if treated as monolithic
- decompose into three channels
 - ordered can show magnitude
 - luminance: how bright
 - saturation: how colorful
 - categorical can show identity
 - hue: what color
- channels have different properties
 - what they convey directly to perceptual system
 - how much they can convey: how many discriminable bins can we use?



<http://www.cs.ubc.ca/~tmm/talks.html#vad21biomedvis>

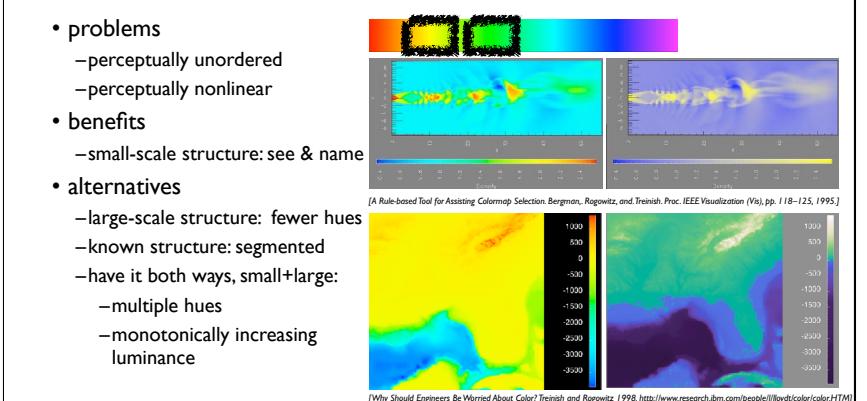
Categorical color: limited number of discriminable bins

- human perception built on relative comparisons
 - great if color contiguous
 - surprisingly bad for absolute comparisons
- noncontiguous small regions of color
 - fewer bins than you want
 - rule of thumb: 6-12 bins, including background and highlights
- alternatives? other talks!



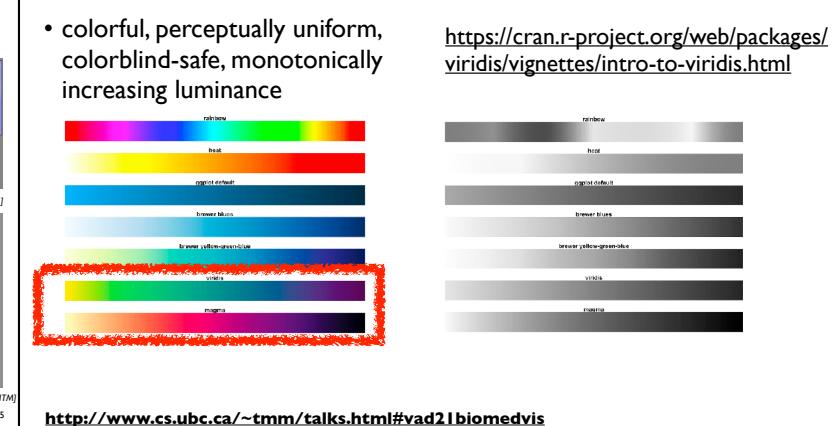
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Ordered color: Rainbow is poor default



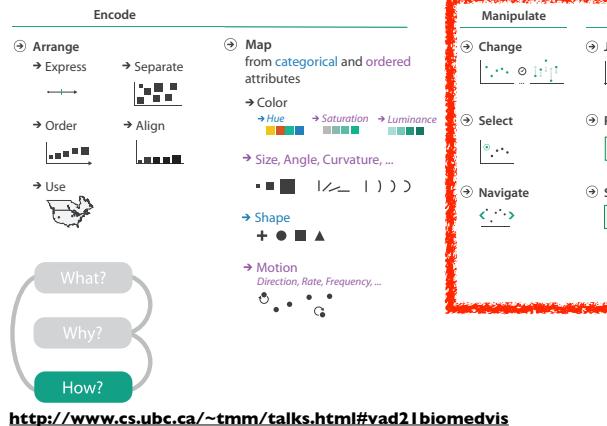
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Viridis / Magma



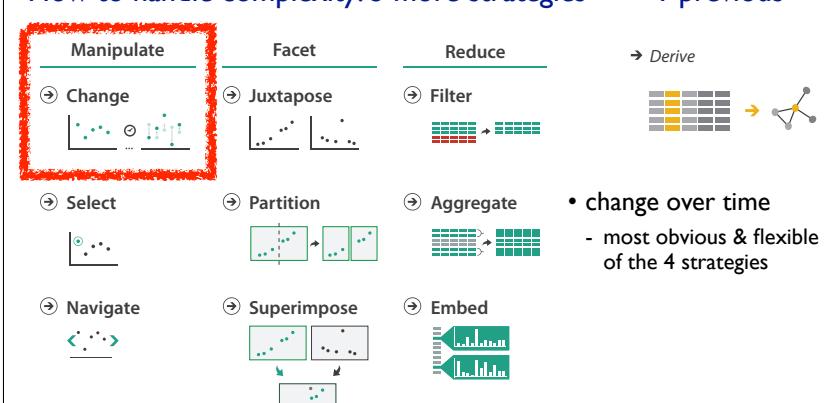
<http://www.cs.ubc.ca/~tmm/talks.html#vad21biomedvis>

How?



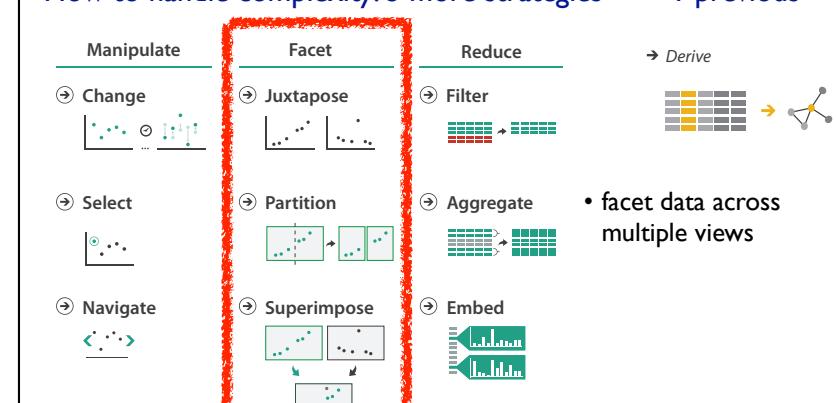
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How to handle complexity: 3 more strategies + I previous



<http://www.cs.ubc.ca/~tmm/talks.html#vad21biomedvis>

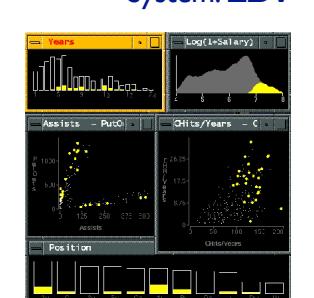
How to handle complexity: 3 more strategies + I previous



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Idiom: Linked highlighting

- see how regions contiguous in one view are distributed within another
 - powerful and pervasive interaction idiom
- encoding: different
- data: all shared



[Visual Exploration of Large Structured Datasets. Wills. Proc. New Techniques and Trends in Statistics (NTTS), pp. 237–246. IOS Press, 1995.]

<http://www.cs.ubc.ca/~tmm/talks.html#vad21biomedvis>

Idiom: bird's-eye maps

- encoding: same
- data: subset shared
- navigation: shared
 - bidirectional linking
- differences
 - viewpoint
 - (size)
- overview-detail



[Review of Overview+Detail, Zooming, and Focus+Context Interfaces. Cockburn, Karlson, and Bederson. ACM Computing Surveys 41:1 (2008), 1–31.]

<http://www.cs.ubc.ca/~tmm/talks.html#vad21biomedvis>

Idiom: Small multiples

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

[\[https://blocks.org/mbstock/1157787\]](https://blocks.org/mbstock/1157787)

Idiom: Small multiples + details on demand

- combining idioms

[\[http://vallandingham.me/co2_small_multiple\]](http://vallandingham.me/co2_small_multiple)

[\[http://vallandingham.me/small_multiples_with_details.html\]](http://vallandingham.me/small_multiples_with_details.html)

Interactive small multiples

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

[\[https://blocks.org/ColinEberhardt/3c780088c363d1515403f50a87a87121\]](https://blocks.org/ColinEberhardt/3c780088c363d1515403f50a87a87121)

[\[https://blog.scotlogic.com/2017/04/05/interactive-responsive-small-multiples.html\]](https://blog.scotlogic.com/2017/04/05/interactive-responsive-small-multiples.html)

[\[http://projects.flowingdata.com/tutlinked_small_multiples_demo/\]](http://projects.flowingdata.com/tutlinked_small_multiples_demo/)

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

Juxtapose vs animate

- animate: hard to follow if many scattered changes or many frames
 - vs easy special case: animated transitions

[Cerebral Visualizing Multiple Experimental Conditions on a Graph with Biological Context. Barsky, Munzner, Gandy, and Kincaid. IEEE Trans. Visualization and Computer Graphics (Proc. InfoVis 2008) 14(6) (2008), 1253–1260.]

Juxtapose vs animate

- animate: hard to follow if many scattered changes or many frames
 - vs easy special case: animated transitions
- juxtapose: easier to compare across small multiples
 - different conditions (color), same gene (layout)

[Cerebral Visualizing Multiple Experimental Conditions on a Graph with Biological Context. Barsky, Munzner, Gandy, and Kincaid. IEEE Trans. Visualization and Computer Graphics (Proc. InfoVis 2008) 14(6) (2008), 1253–1260.]

View coordination: Design choices

		Data		
		All	Subset	None
Encoding	Same	Redundant	Overview/ Detail	Small Multiples
		Multiform	Multiform, Overview/ Detail	No Linkage
		Manipulate	Facet	Reduce
@ Change		@ Juxtapose	@ Filter	@ Derive
@ Select		@ Partition	@ Aggregate	
@ Navigate		@ Superimpose	@ Embed	

How to handle complexity: 3 more strategies

- + 1 previous
- reduce what is shown within single view

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, facet, change, derive

Reducing Items and Attributes

- Reduce
- Filter → Items
- Filter → Attributes
- Aggregate → Items
- Aggregate → Attributes

Idiom: boxplot

- static item aggregation
- task: find distribution
- data: table
- derived data
 - 5 quant attrs
 - 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]

Spatial aggregation

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

[\[http://www.e-education.psu.edu/geog486/l4/p7.html Fig 4.cg.6\]](http://www.e-education.psu.edu/geog486/l4/p7.html)

[\[https://blog.cartographica.com/blog/2011/5/19/the-modifiable-area-unit-problem-in-gis.html\]](https://blog.cartographica.com/blog/2011/5/19/the-modifiable-area-unit-problem-in-gis.html)

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 → Benign

data: 9D measured space

derived data: 2D target space

Idiom: Dimensionality reduction for documents

Task 1: Item 1, Item ... , Item n → In HD data → Out 2D data. What? In High-dimensional data. Why? Produce. How? Derive.

Task 2: Item 1, Item ... , Item n → In 2D data → Out Scatterplot Clusters & points. What? In 2D data. Why? Discover. How? Encode.

Task 3: Item 1, Item ... , Item n → In 2D data → Out Scatterplot Clusters & points → Labels for clusters. What? In Scatterplot Clusters & points. Why? Explore. How? Navigate.

What? In Clusters & points. Why? Identify. How? Select points.

More Information

@tamaramunzner

- this talk <http://www.cs.ubc.ca/~tmm/talks.html#vad21biomedvis>
- book page (including tutorial lecture slides) <http://www.cs.ubc.ca/~tmm/vadbook>
 - 20% promo code for book+ebook combo: HVN17
 - <http://www.crcpress.com/product/isbn/9781466508910>
- illustrations: Eamonn Maguire
- papers, videos, software, talks, courses
 - <http://www.cs.ubc.ca/group/infovis>
 - <http://www.cs.ubc.ca/~tmm>

Visualization Analysis and Design. Munzner. A K Peters Visualization Series, CRC Press, Visualization Series, 2014.