# **Visualization Principles**

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Cytoscape Symposium on Network Biology 2012 13 Dec 2012

 $http://www.cs.ubc.ca/{\sim}tmm/talks.html\#networkbio\ I\ 2$ 

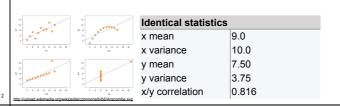
### Defining visualization

computer-based visualization systems provide visual representations of datasets intended to help people carry out some task more effectively

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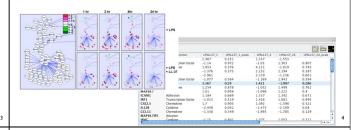
• human in the loop needs the details



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  - external representation: perception vs cognition



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- human in the loop needs the details
- external representation: perception vs cognition
- intended task
- measureable definitions of effectiveness

### Defining visualization

Computer-based visualization systems provide visual representations of datasets intended to help people carry out some task more effectively.

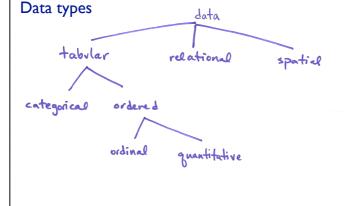
These visualization systems are often but not always interactive. Resource limitations include the capacity of computers, of humans, and of displays.

### Visualization design space

- huge space of design alternatives
- -tradeoffs abound
- many possibilities now known to be ineffective
  - avoid random walk through parameter space
  - · avoid some of our past mistakes
  - extensive experimentation has already been done
- guidelines continue to evolve
- -we reflect on lessons learned in design studies
- -iterative refinement usually wise

### **Principles**

- know your visual channel types and ranks
- categorical color constraints
- power of the plane
- danger of depth
- resolution beats immersion
- eyes beat memory
- validate against the right threat



Data types

tabular relational spatial

categorical ordered

fruit:
apples, oranges ordinal quantitative

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fruit:
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# Data types tabular relational spatial categorical ordered fruit: apples, oranges ordinal quantitative shirt-sizes: small, medium, longe 17-inches, 23 inches

Data types

tabular relational spatial
links between
table columns

categorical ordered

fruit:
apples, pranges
ordinal
shirt-siges:
small, medium, large 17-inches, 23 inches

Data types data tabular relational spatial links between intrinsic position table columns not abstract categorical ordered fruit: apples, oranges ordinal quantitative shirt sizes: lengths: 17 inches, 23 inches

# Visual encoding

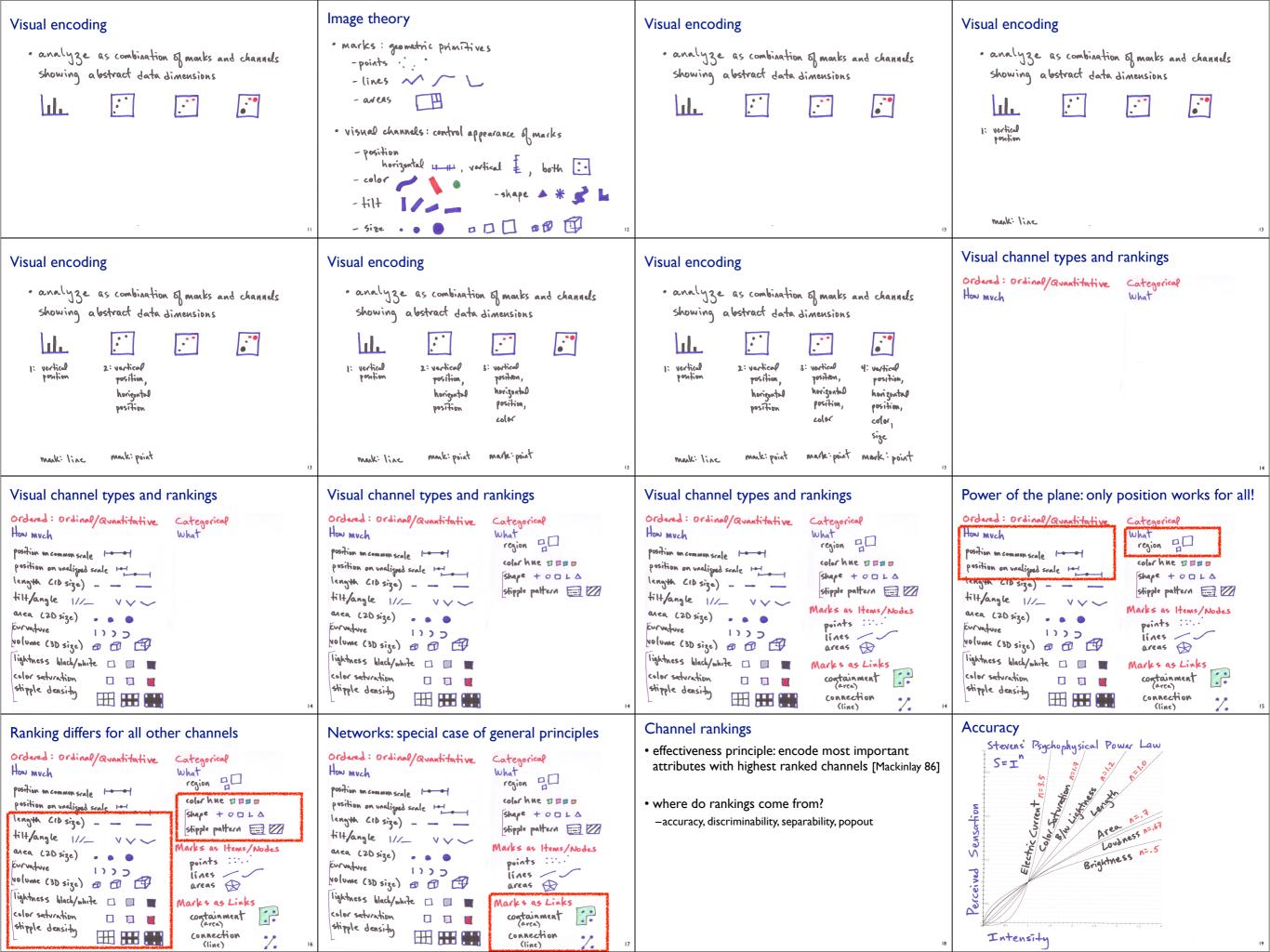
· analyze
showing abstract data dimensions



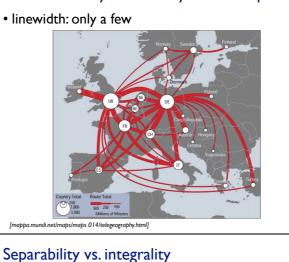


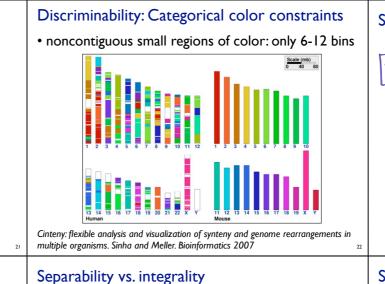


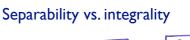




# Discriminability: How many usable steps? Accuracy · position along common scale - frame increases accuracy [cleveland 84] - Weber's Law: relative judgements filled rectangles differ by 1:9 white rectangles differ by 1:2















### Separability vs. integrality



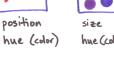
fully separable











fully separable

2 groups each

position

hue (color)

fully separable

Separability vs. integrality

size

hue (color)

interference

difficult to

discriminate

small Hems

2 groups each





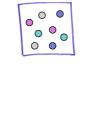
interference

difficult to

discriminate

small Hems

2 groups each



000

0 0

red

green

major interference

integral

percept:

color/hne

4 groups

000



position

hue (color)



Popout: Most channels

-sufficiently different item

independent of distractor

noticed immediately,

· some channels have no

popout: serial search

Healey. Perception in Visualization

http://www.csc.ncsu.edu/faculty/healey/PP/

parallel processing on

most channels

count

required

interference

difficult to

discriminate

..

hue (color)

size







integral percept: (planar size)

3 groups





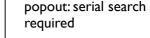












Curvemap



# Separability vs. integrality



fully separable

2 groups each



interference

difficult to

discriminat

small items

2 groups each







some/significant

interference

area



integral percept: color/hue Lplanar size

4 groups 3 groups

### Separability vs. integrality



fully separable

2 groups each

**Popout limits** 

2 groups each







discriminate

small items

2 groups each





size: width

size: height





major interference

000

**0 0** .

0 0

red

0





## Encoding example: Heatmaps vs. curvemaps

size: width

size: height

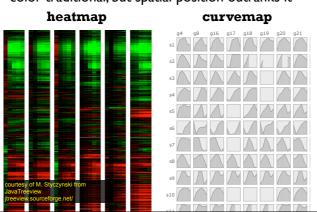
some/significan

interference

integral percept:

3 groups

• color traditional, but spatial position outranks it heatmap curvemap



### Curvemap

· shape perception easier for filled framed line charts than colored boxes

Pathline: A Tool for Comparative Functional Genomics.

Meyer, Wong, Styczynski, Munzner, Pfister. EuroVis 2010.



### noticed immediately,

• parallel processing on

most channels

Popout: Most channels

- -sufficiently different item independent of distractor count
- some channels have no popout: serial search









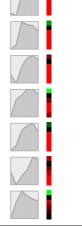


# · shape perception easier for

filled framed line charts than colored boxes

Pathline: A Tool for Comparative Functional Genomics.

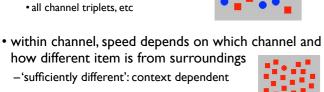
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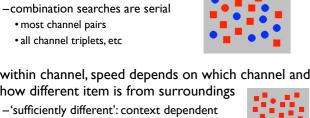


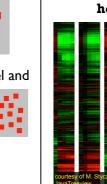
Healey. Perception in Visualization http://www.csc.ncsu.edu/faculty/healey/PP/

• only one channel at a time

most channel pairs







# Curvemap shape perception easier for filled framed line charts than colored boxes Pathline: A Tool for Comparative Functional Genomics. Meyer, Wong, Styczynski, Munzner, Pfister. EuroVis 2010.

### Dangers of depth

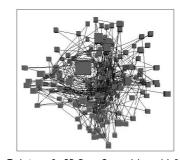
- rankings for **planar** spatial position, not depth!
- we don't really live in 3D: we see in 2.05D
- -up/down and sideways: image plane
- · acquire more info quickly from eye movements
- -away: depth into scene
- · only acquire more info from head/body motion



 further reading Visual Thinking for Design (Chap 5). Colin Ware. 2008

### Dangers of depth: difficulties of 3D

- occlusion
- interaction complexity



Distortion Viewing Techniques for 3D Data. Carpendale et al. InfoVis I 996.

### Dangers of depth: difficulties of 3D

- perspective distortion
- -interferes with all size channel encodings
- -power of the plane is lost!

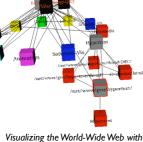


Visualizing the Results of Multimedia Web Search Engines. Mukherjea, Hirata, and Hara. InfoVis 96

### Dangers of depth: difficulties of 3D

- tilted text isn't legible
- -far worse when tilted from image plane
- further reading

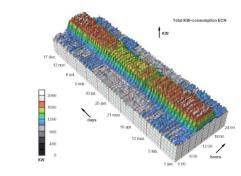
Exploring and Reducing the Effects of Orientation on Text Readability in Volumetric Displays. Grossman et al. CHI 2007



the Navigational View Builder. Mukherjea and Foley. Computer Networks and ISDN Systems, 1995.

### Dangers of depth example

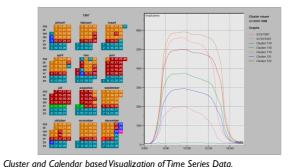
• extruded curves: detailed comparisons impossible



Cluster and Calendar based Visualization of Time Series Data. van Wijk and van Selow, Proc InfoVis 99.

### Transformation to suitable abstraction

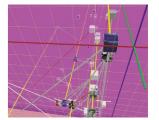
- derived data: clusters
- multiple views: calendar, superimposed 2D curves



van Wijk and van Selow, Proc InfoVis 99.

### Dangers of depth: must justify

- 3D legitimate for true 3D spatial data
- 3D needs very careful justification for abstract data
- enthusiasm in 1990s, but now skepticism
- be especially careful with 3D for point clouds or networks



WEBPATH-a three dimensional Web history. Frecon and Smith. InfoVis 1999

### Pixels are precious: Resolution beats immersion

- immersion typically not helpful for abstract data
- -do not need sense of presence or stereoscopic 3D
- resolution much more important
- -pixels are the scarcest resource
- -desktop also better for workflow integration
- · virtual reality for abstract data very difficult to justify





Development of an information visualization tool using virtual reality. Kirner and Martins. Symp Applied Computing 2000

### Eyes beat memory

- principle: external cognition vs. internal memory
  - -easy to compare by moving eyes between side-by-side views -harder to compare visible item to memory of what you saw
  - implications for animation
  - -great for choreographed storytelling
  - -great for transitions between two states
  - -poor for many states with changes everywhere

· consider small multiples instead abstract

animation small multiples show time with time show time with space

### Small multiples example: Cerebral

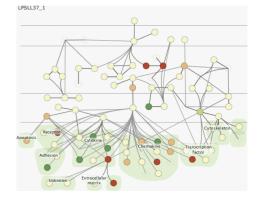
- · small multiples: one graph instance per experimental condition
  - -same spatial layout
  - -color differently, by condition



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

### Why not animation?

• global comparison difficult



### Why not animation?

further reading

Animation: can it facilitate? Tversky et al. Intl Journ Human-Computer Studies, 57(4):247-262, 2002.

### Beyond encoding and interaction

- three more levels of design questions
  - -different threats to validity at each level

problem: you misunderstood their needs

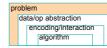
validate against the right threat

abstraction: you're showing them the wrong thing encoding: the way you show it doesn't work

algorithm: your code is too slow

A Nested Model for Visualization Design and Validation. Munzner. IEEE InfoVis 2009.

### Characterizing problems of real-world users



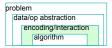
- identify a problem amenable to vis
- -provide novel capabilities
- -speed up existing workflow
- -immediate: interview and observe target users
- -downstream: notice adoption rates

### Abstracting into operations on data types

data/op abstraction

- abstract from domain-specific to generic
- operations
  - sorting, filtering, browsing, comparing, finding trend/outlier, characterizing distributions, finding correlation...
- data types
- validation
- tables, networks, spatial - transform into useful configuration: derived data
  - -deploy in the field and observe usage

# Designing visual encoding, interaction techniques



- visual encoding: drawings they are shown
- interaction: how they manipulate drawings
- validation
- -immediate: careful justification wrt known principles
- -downstream: qualitative or quantitative analysis of results
- -downstream: lab study measuring time/error on given task
- focus of this talk

### Creating algorithms to execute techniques



- automatically carry out specification
- validation
- -immediate: complexity analysis
- -downstream: benchmarks for system time, memory

### Danger of validation mismatch

- cannot show encoding good with system timings
- · cannot show abstraction good with lab study



### Principles recap

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More information

 this talk <a href="http://www.cs.ubc.ca/~tmm/talks.html#networkbio12">http://www.cs.ubc.ca/~tmm/talks.html#networkbio12</a>

- papers, videos, software, talks, courses <a href="http://www.cs.ubc.ca/~tmm">http://www.cs.ubc.ca/~tmm</a>
- · vis intro book chapter
- -principles in more depth
- -also, techniques!

http://www.cs.ubc.ca/~tmm/papers.html#akpchapter

- textbook to appear early 2014
- Visualization Analysis and Design: Abstractions, Principles, and Methods

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