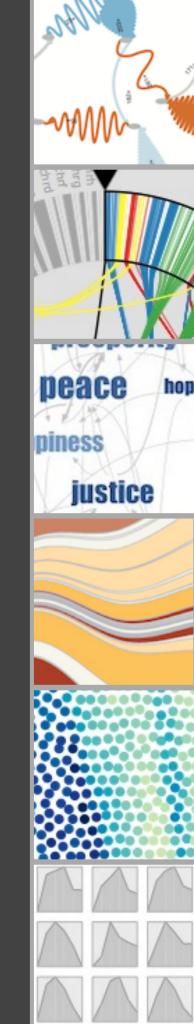
VISUAL ENCODING

Miriah Meyer University of Utah

slide acknowledgements:

Tamara Munzner, University of British Columbia Hanspeter Pfister, Harvard University Bang Wong, Broad Institute 2



LASTTIME

DATASET TYPES

tables

networks

text/logs

Α	В	С	S	Т	U
Order ID	Order Date	Order Priority	Product Container	Product Base Margin	Ship Date
3	10/14/06	5-Low	Large Box	0.8	10/21/06
6	2/21/08	4-Not Specified	Small Pack	0.55	2/22/08
32	7/16/07	2-High	Small Pack	0.79	7/17/07
32	7/16/07	2-High	Jumbo Box	- 4.4	7/17/07
32	7/16/07	2-High	Medium Box	attribute	7/18/07
32	7/16/07	2-High	Medium Box	0.03	7/18/07
35	10/23/07	4-Not Specified	Wrap Bag	0.52	10/24/07
35	10/23/07	4-Not Specified	Small Box	0.58	10/25/07
•	1/3/07	1-Urgent	Small Box	0.55	11/3/07
IT	em /18/07	1-Urgent	Small Pack	0.49	3/19/07
סס	/20/05	5-Low	Wrap Bag	0.56	1/20/05
69	6/4/05	4-Not Specified	Small Pack	0.44	6/6/05
69	6/4/05	4-Not Specified	Wrap Bag	0.6	6/6/05
70	12/18/06	5-Low	Small Box	0.59	12/23/06
70	12/18/06	5-Low	Wrap Bag	0.82	12/23/06
96	4/17/05	2-High	Small Box	0.55	4/19/05
97	1/29/06	3-Medium	Small Box	0.38	1/30/06
129	11/19/08	5-Low	Small Box	0.37	11/28/08
130	5/8/08	2-High	Small Box	0.37	5/9/08
130	5/8/08	2-High	Medium Box	0.38	5/10/08
130	5/8/08	2-High	Small Box	0.6	5/11/08
132	6/11/06	3-Medium	Medium Box	0.6	6/12/06
132	6/11/06	3-Medium	Jumbo Box	0.69	6/14/06
134	5/1/08	4-Not Specified	Large Box	0.82	5/3/08
135	10/21/07	4-Not Specified	Small Pack	0.64	10/23/07
166	9/12/07	2-High	Small Box	0.55	9/14/07
193	8/8/06	1-Urgent	Medium Box	0.57	8/10/06
194	4/5/08	3-Medium	Wrap Bag	0.42	4/7/08

ATTRIBUTE TYPES mathematical interpretation Categorica ordered quantitative seguential diverging

ATTRIBUTE SEMANTICS

DATASET SEMANTICS

real-world meaning visualization specific

DATA vs CONCEPTUAL MODEL

- -from data model . . .
 - -32.52, 54.06, -17.35, . . . (floats)
- -using conceptual model . . .
 - -temperature
- -to data type.
 - -continuous to 2 significant figures (Q)
 - -hot, warm, cold (O)
 - -above freezing, below freezing (C)

-relativity of perception

-marks and channels

-planar position

-color

target translate design implement validate

comments on readings?

-relativity of perception

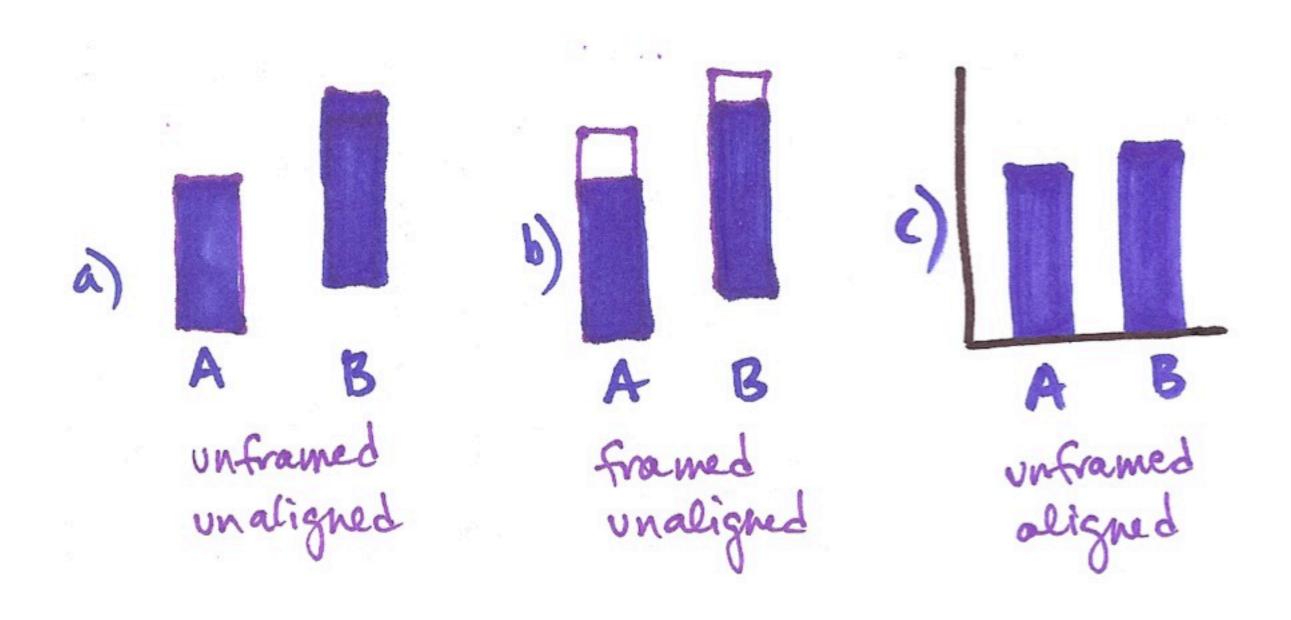
-marks and channels

-planar position

-color

WEBER'S LAW

we judge based on relative, not absolute, differences

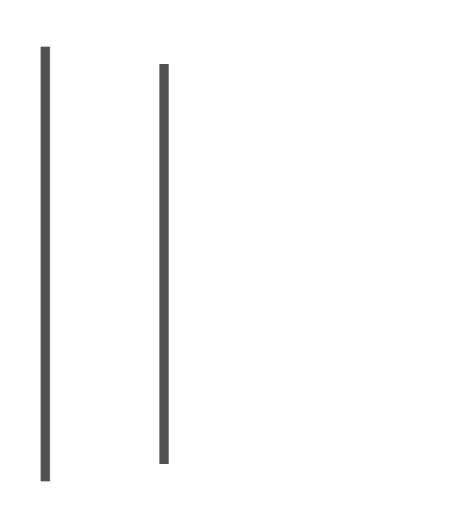


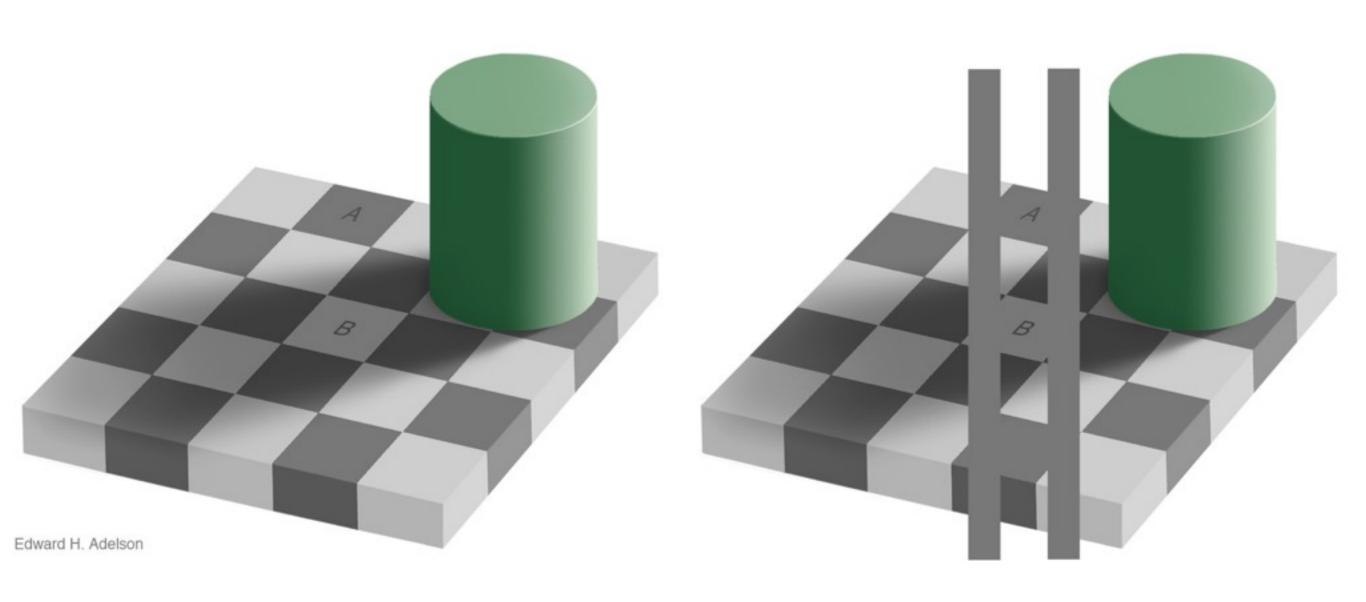
RELATIVE DIFFERENCES

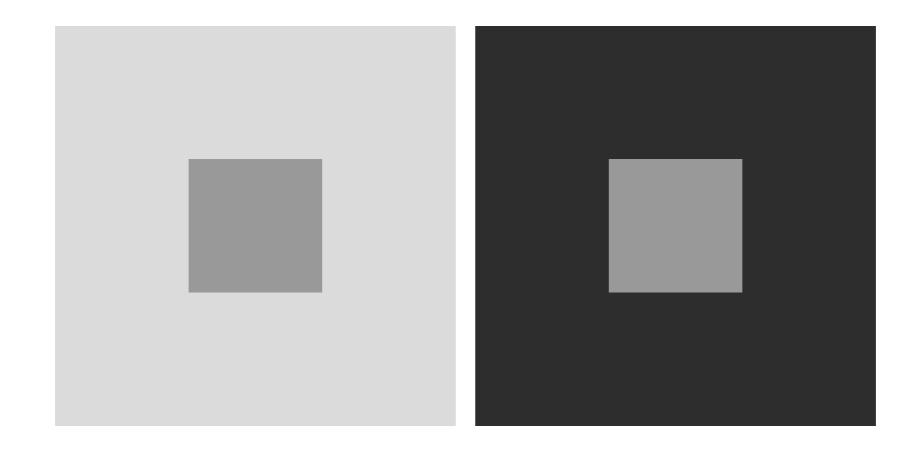


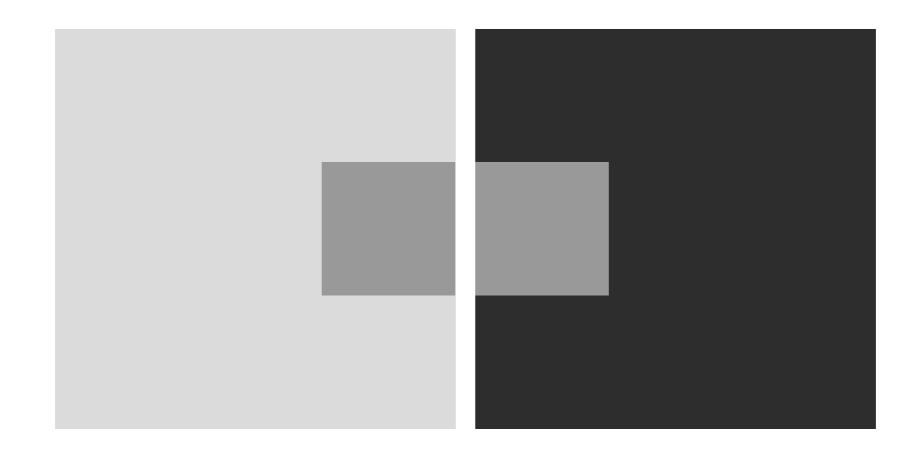
AXIS OF ALIGNMENT

AXIS OF ALIGNMENT

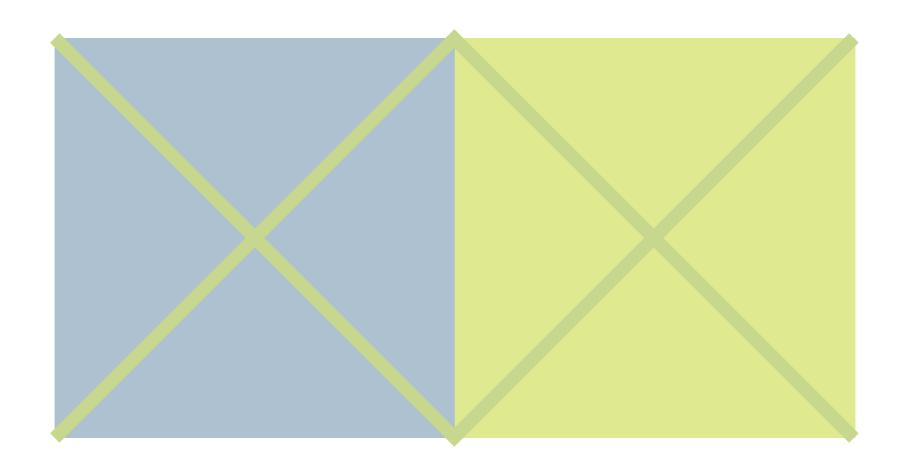


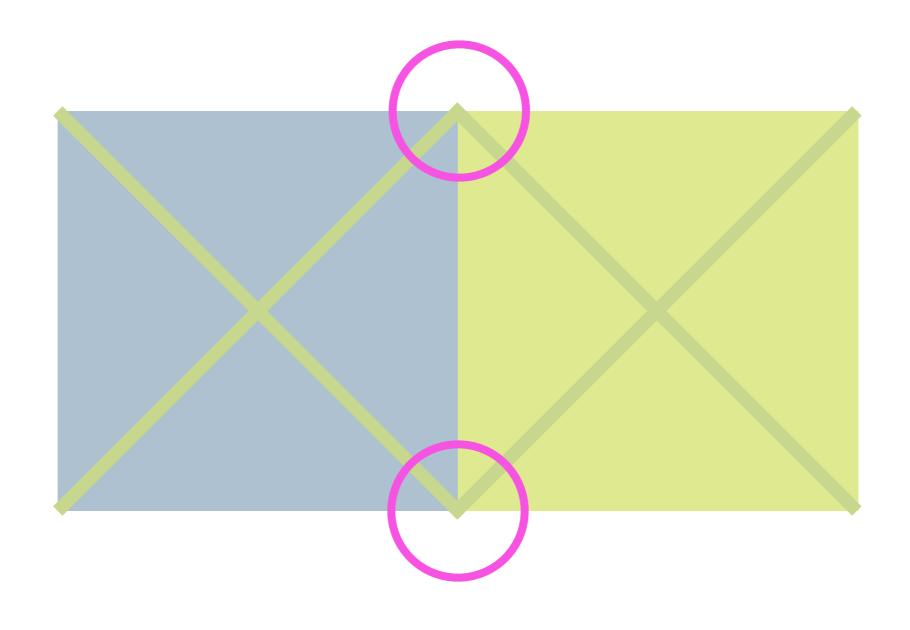


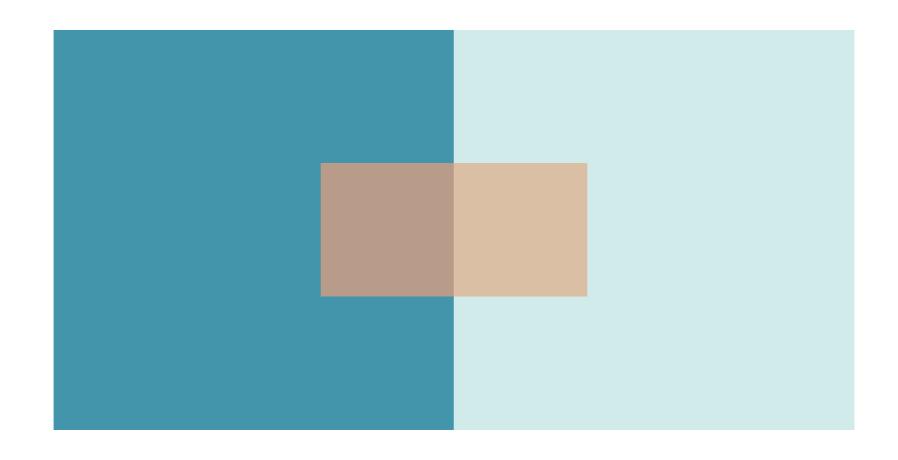


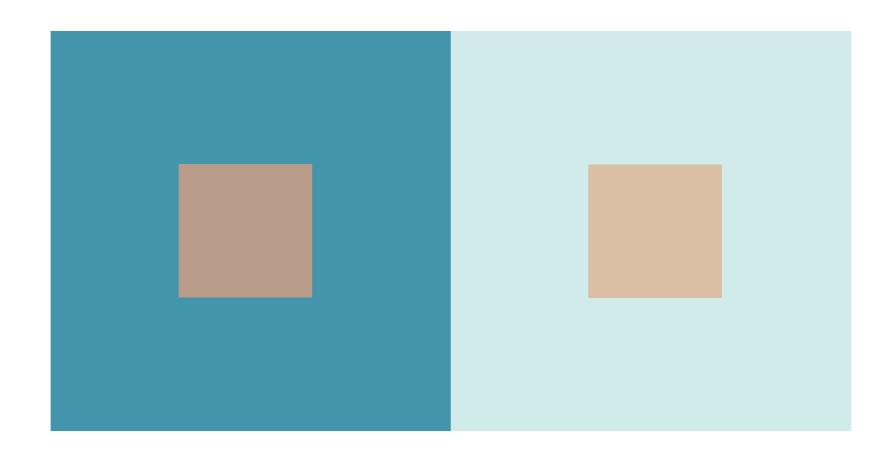


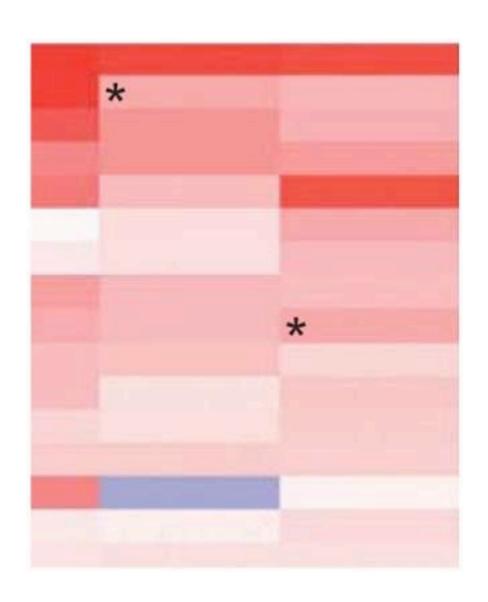












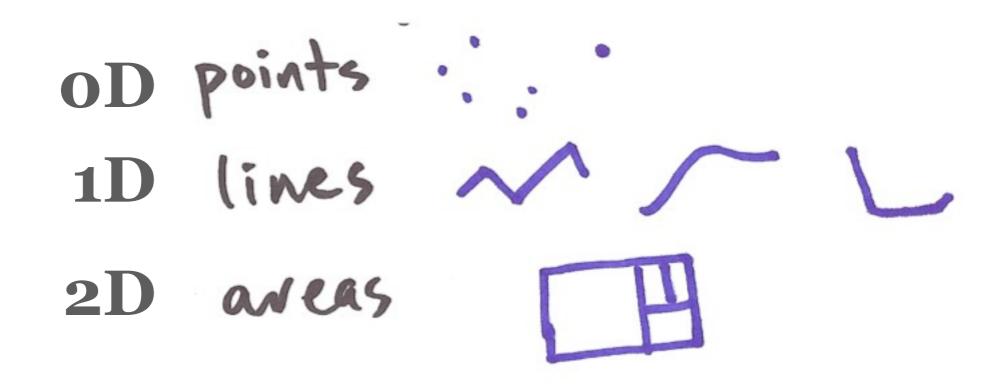
-relativity of perception

-marks and channels

-planar position

-color

MARKS geometric primitives



CHANNELS

parameters that control the appearance of marks

categorical What /where effectiveness

planer position ...

stipple pattern





ordinal | quantitative

How much

position on common scale position on unaligned scale length CID size) tilt, angle

area (2D size) networks | same category

Grouping

Containment (2D)

Connection (ID)

Similarity Cother channels)

Proximity (position)



volume (3D size)



color saturation stipple density







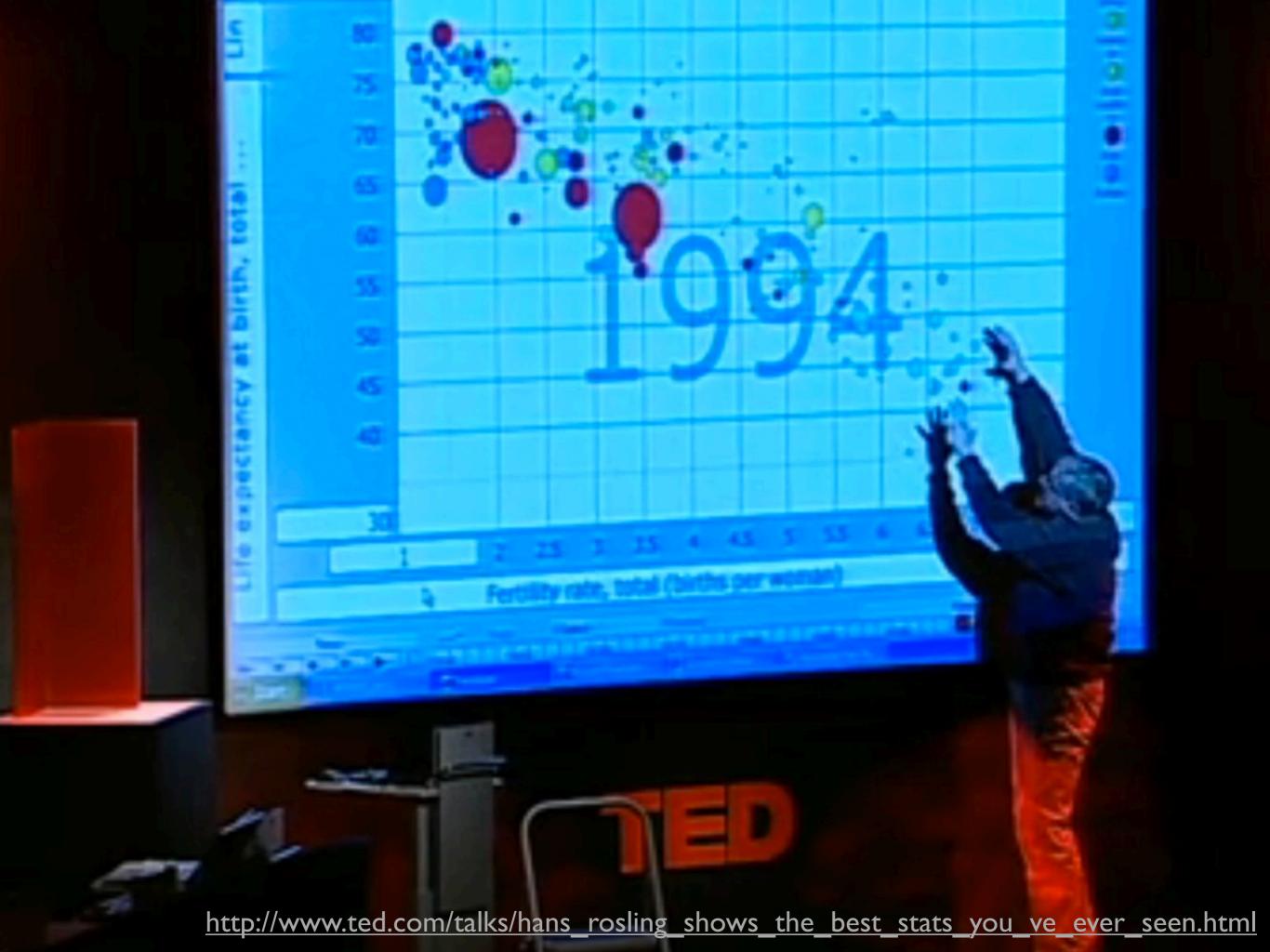


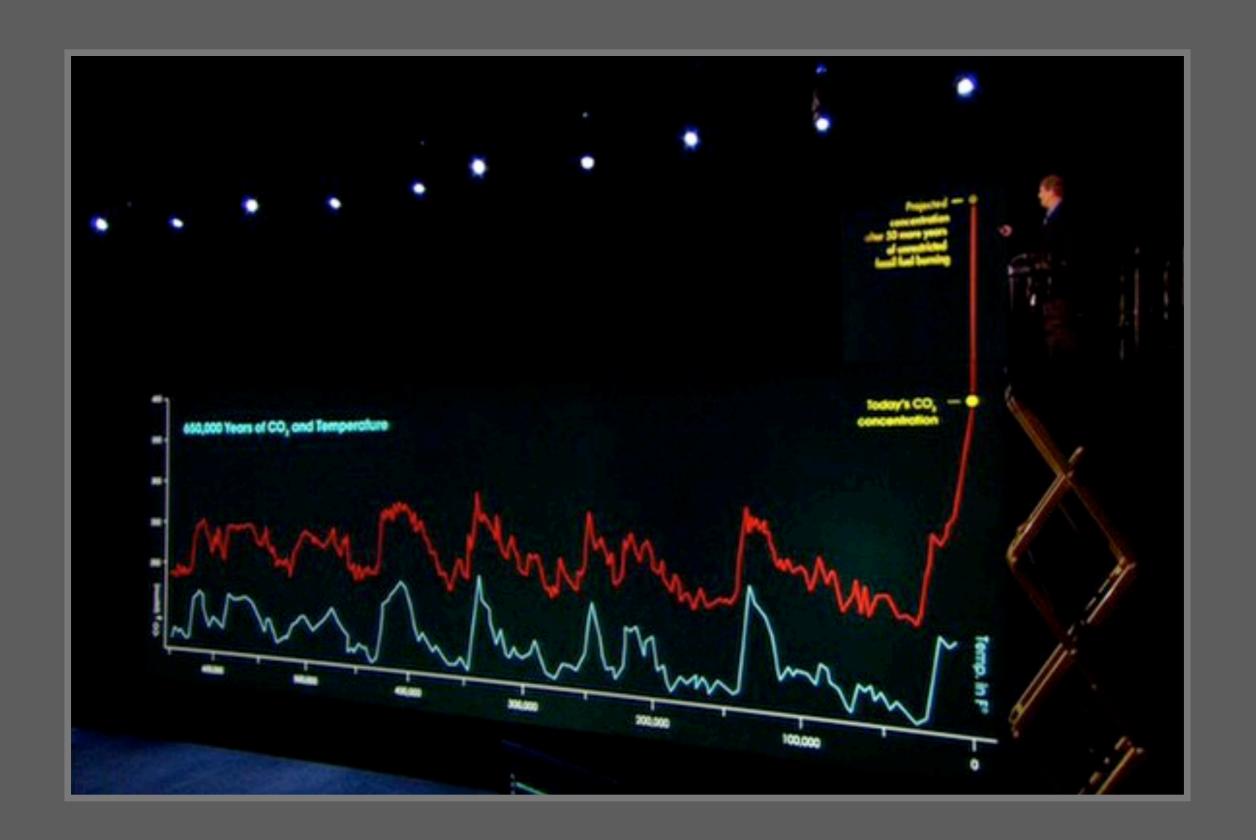






name that channel ...

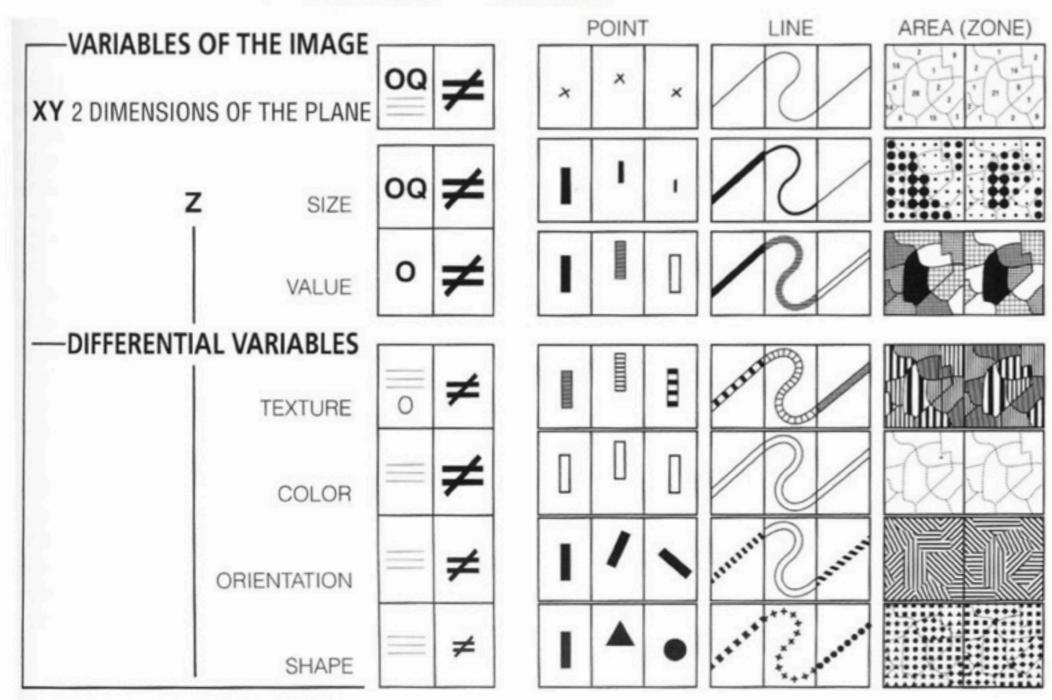




WHERE DO RANKINGS COME FROM?

Bertin, 1967

O = Ordinal, Q = Quantitative ≠ = Differences = = Similarities



Cleveland & McGill, 1984

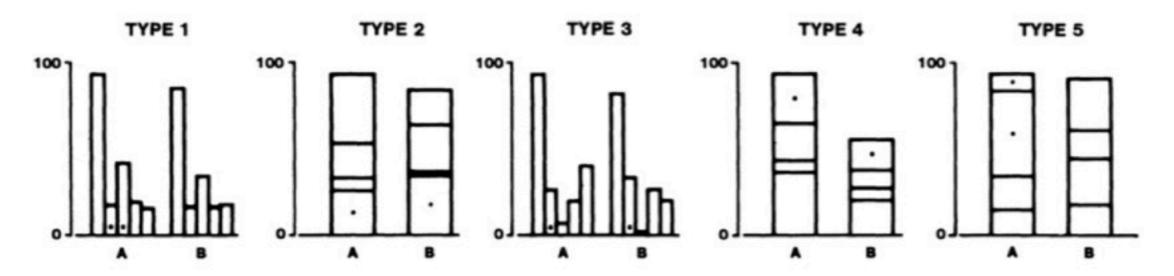


Figure 4. Graphs from position-length experiment.

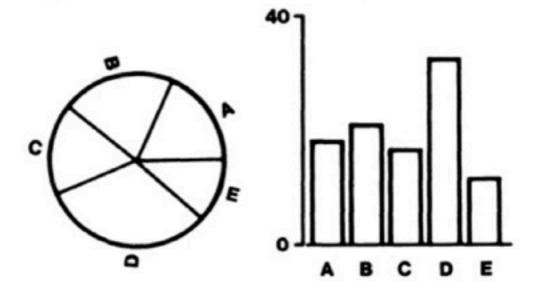


Figure 3. Graphs from position-angle experiment.

Heer & Bostock, 2010

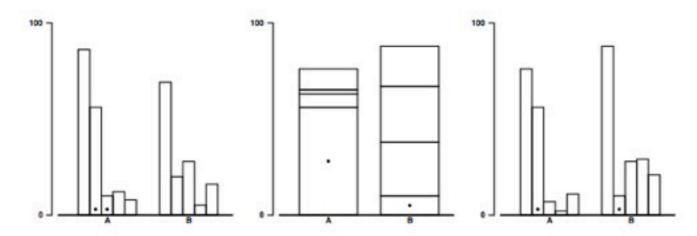


Figure 1: Stimuli for judgment tasks T1, T2 & T3. Subjects estimated percent differences between elements.

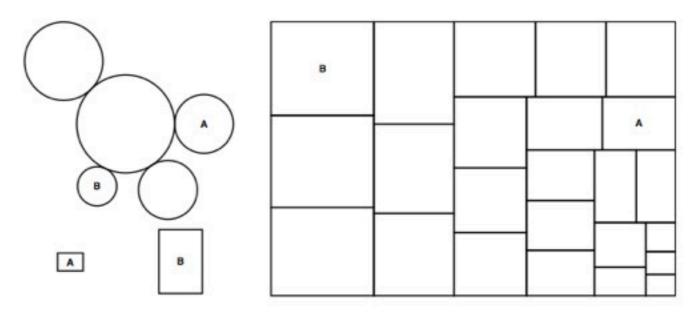
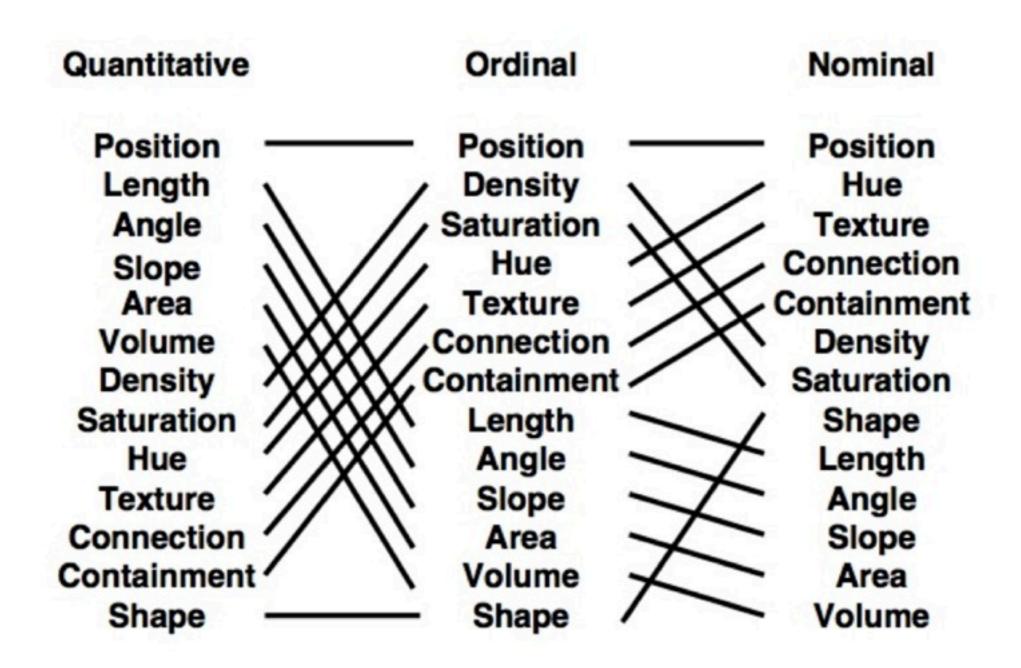
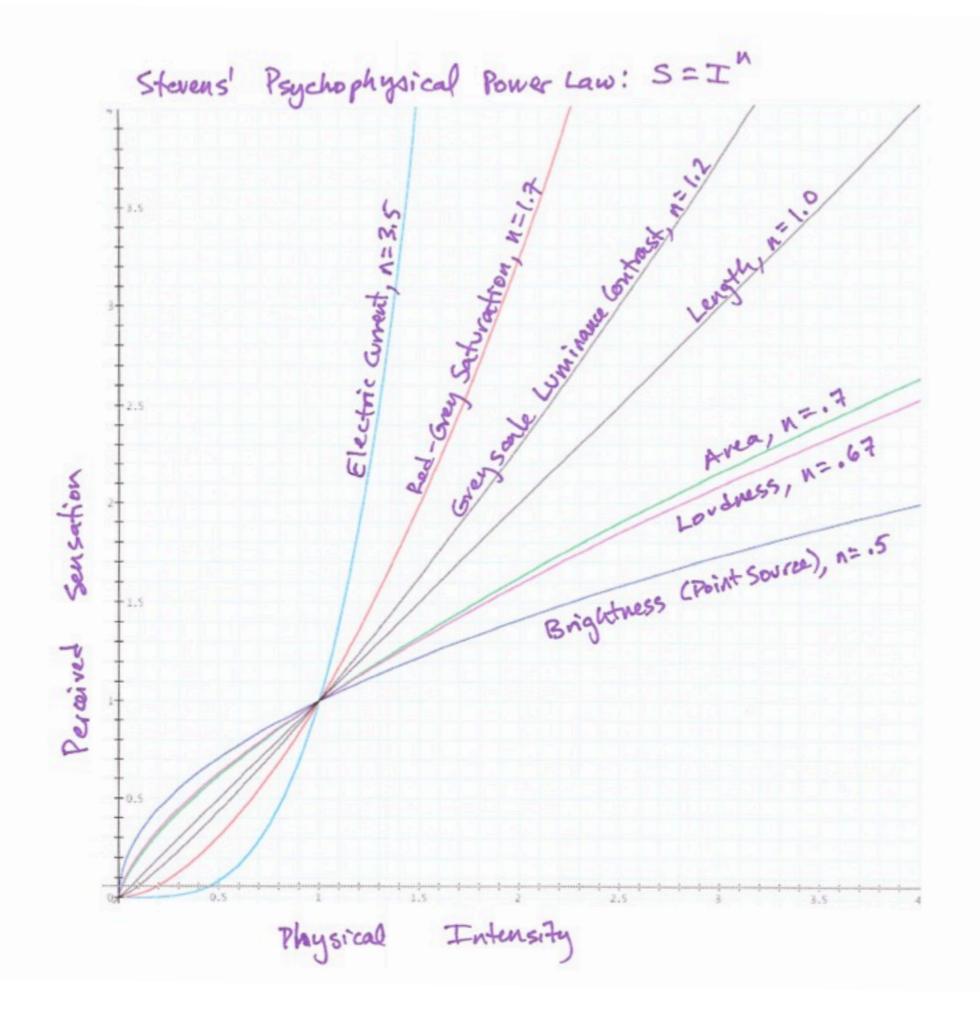


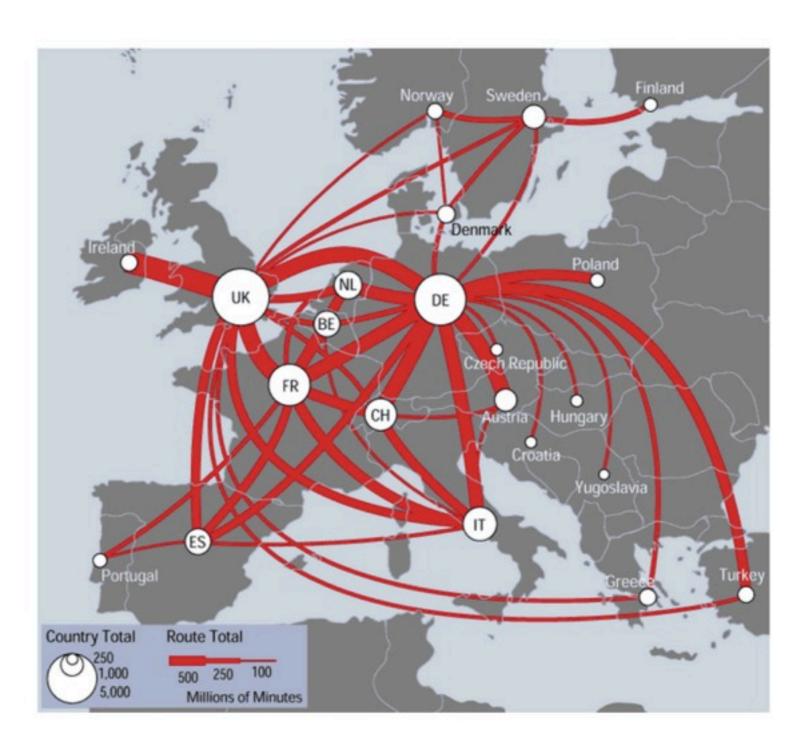
Figure 2: Area judgment stimuli. Top left: Bubble chart (T7), Bottom left: Center-aligned rectangles (T8), Right: Treemap (T9).

Mackinlay, 1986





DISCRIMINABILITY can channel differences be discerned?

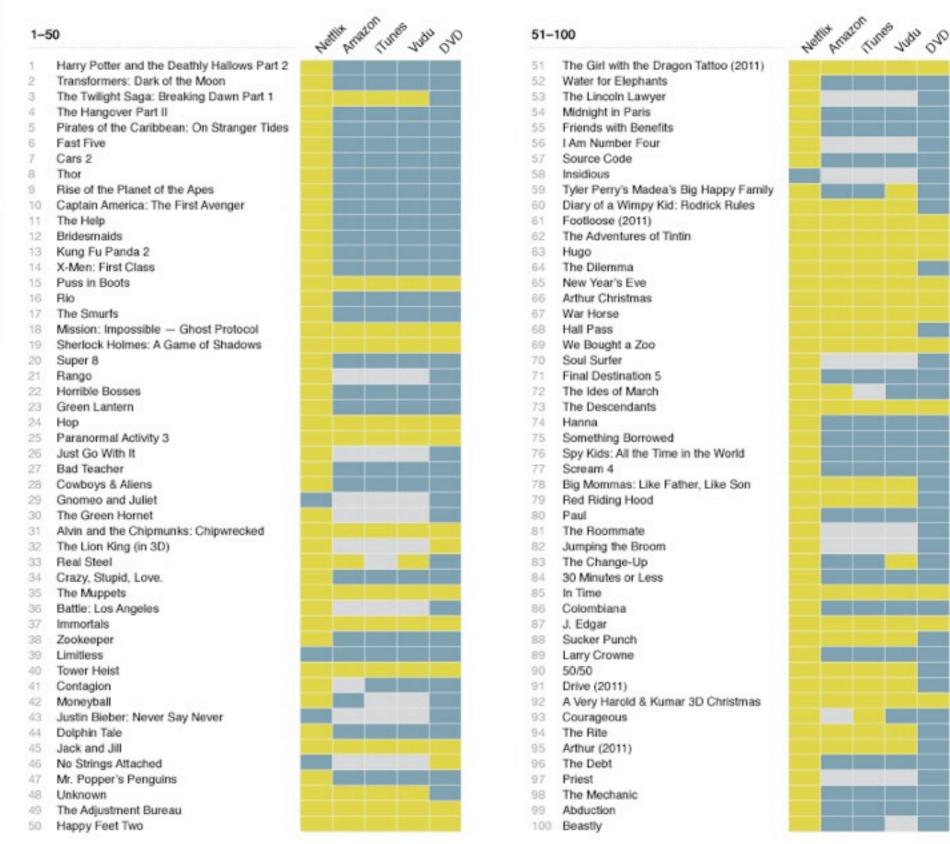


Streaming the Box Office



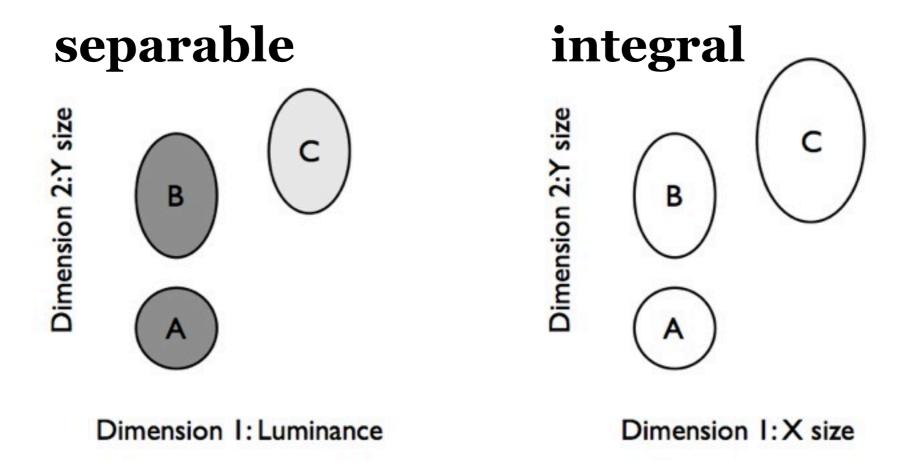
Tristan Louis compiled a list of the top 100 movies at the box office, according to Box Office Mojo, that were available streaming. This is a graphical version of that list.

Source: Tristan Louis By: Nathan Yau



SEPARABLE vs INTEGRAL

- -separable: can judge each channel individually
- -integral: two channels are viewed holistically



SEPARABLE vs INTEGRAL

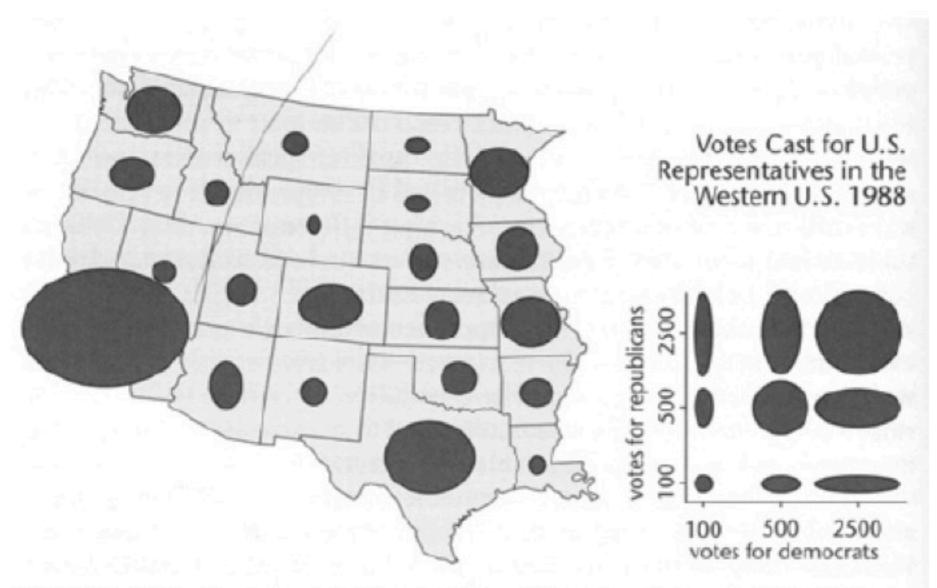
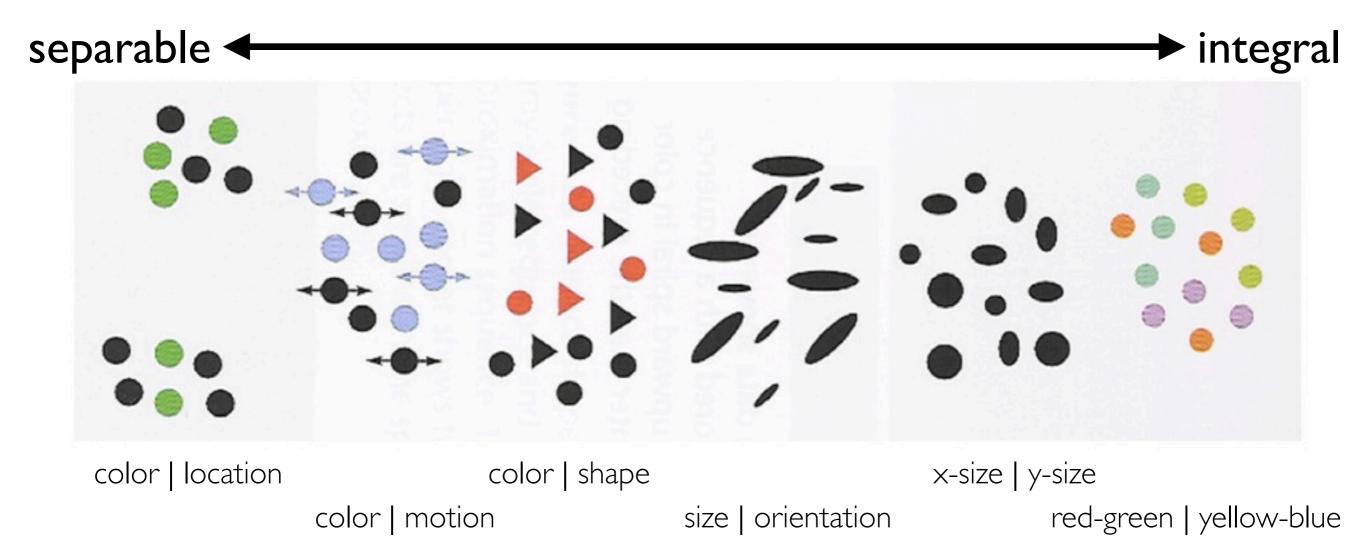
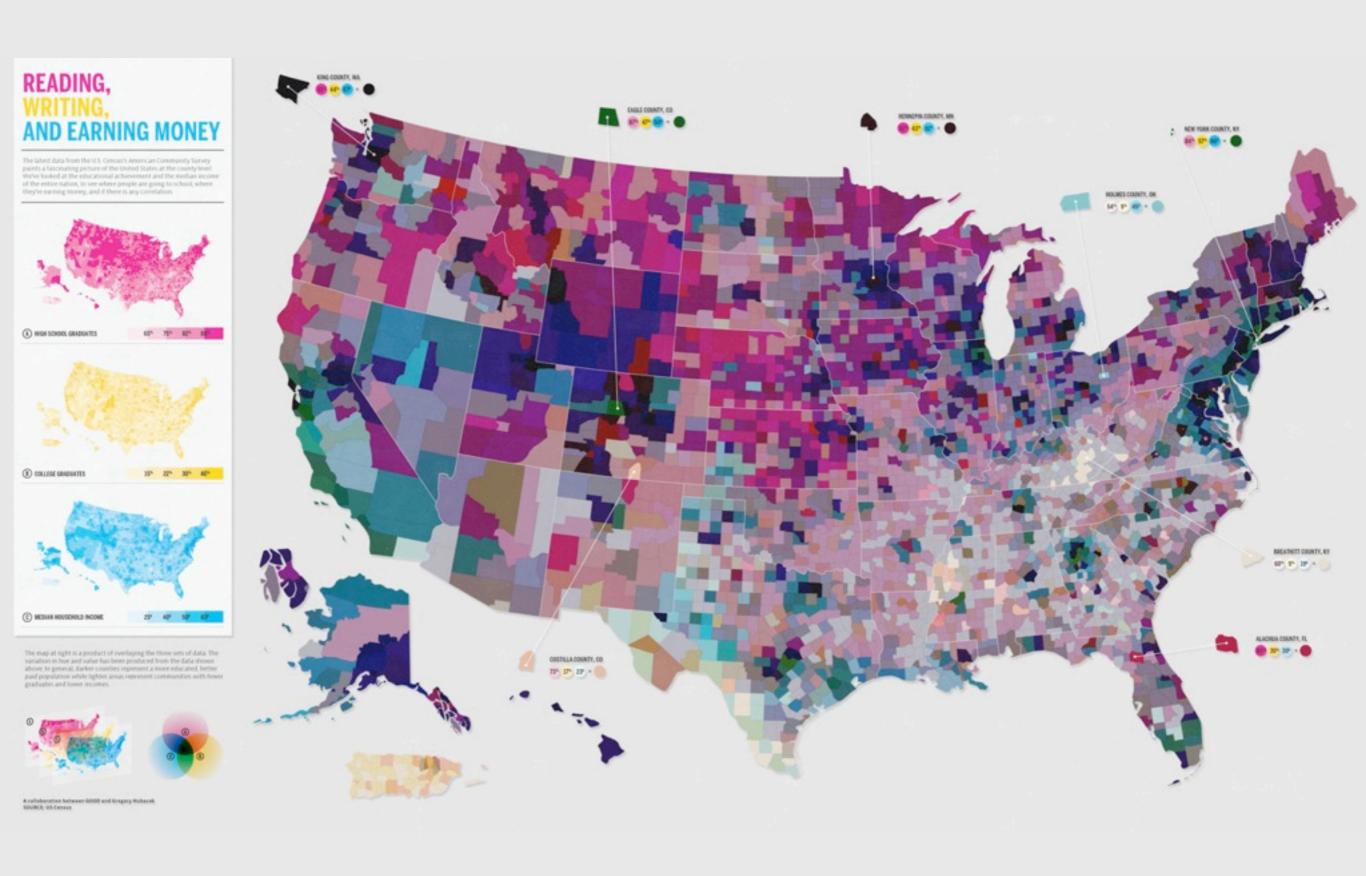


FIGURE 3.38. An example of the use of an ellipse as a map symbol in which the horizontal and vertical axes represent different (but presumably related) variables.

SEPARABLE vs INTEGRAL





http://www.good.is/post/america-s-richest-counties-and-best-educated-counties/

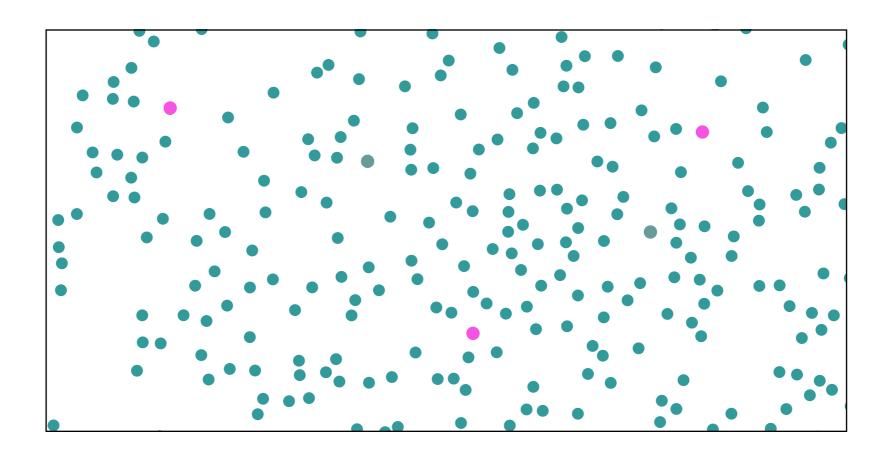
PRE-ATTENTIVE PROCESSING

-requires attention, despite name

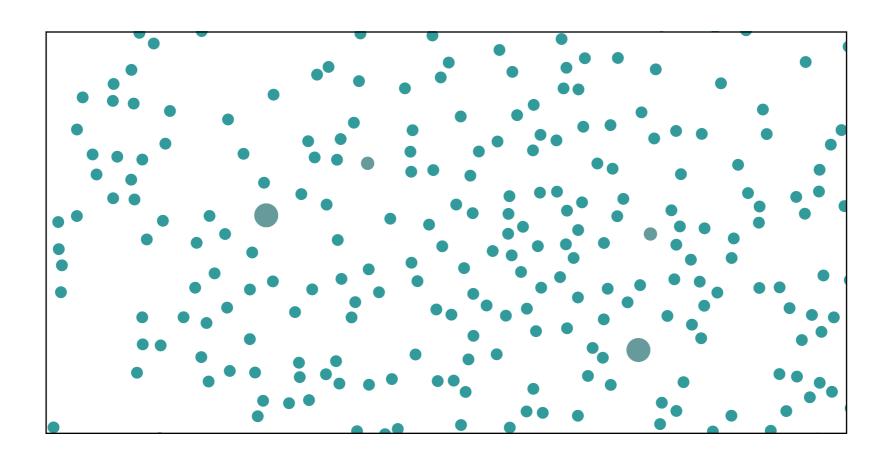
-very fast: <200 ms

-what matters most is contrast between features

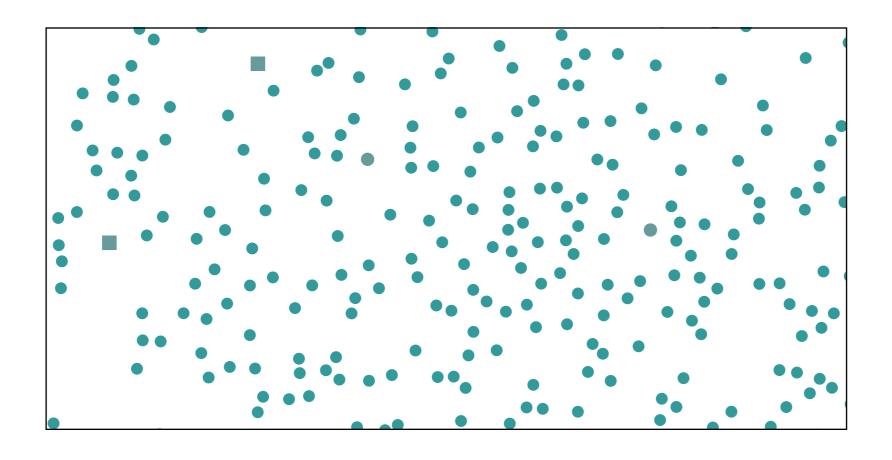
POPOUT



POPOUT



POPOUT

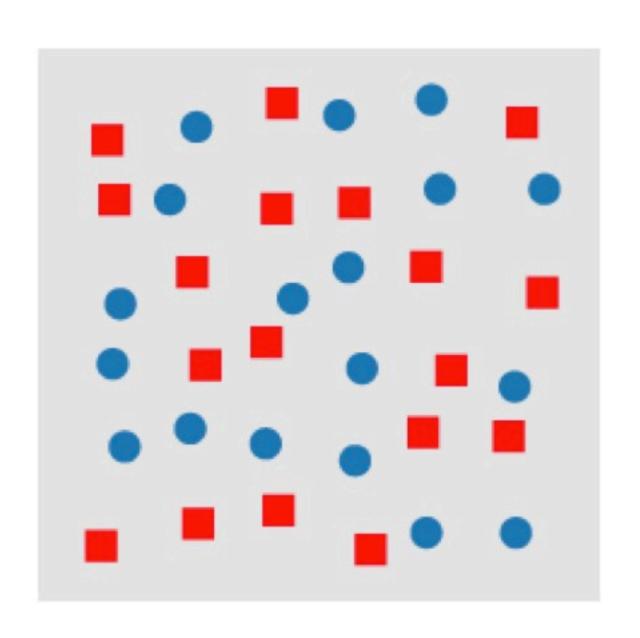


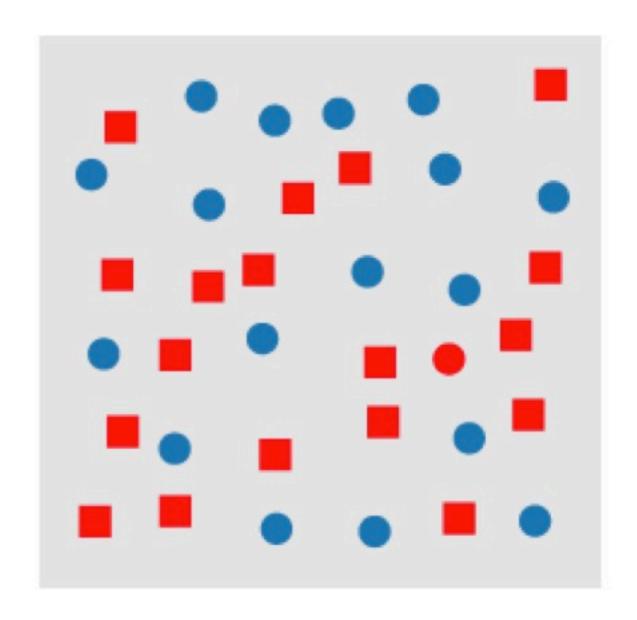
lightness hue Color elongation size Elementary shape orientation Motion Spatial grouping

BASIC POPOUT

CHANNELS

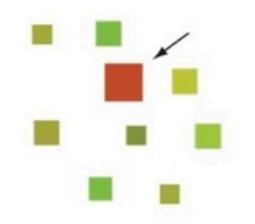
CONJUNCTION or, why to use a single channel at a time

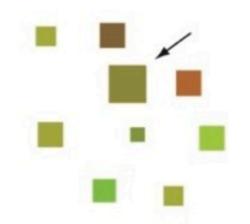


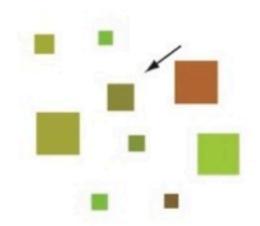


CONJUNCTION

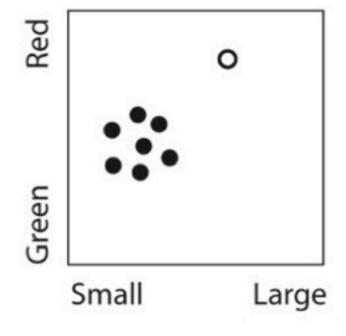
objects to be searched

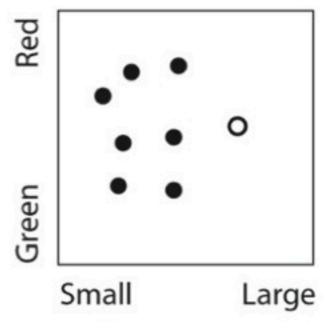


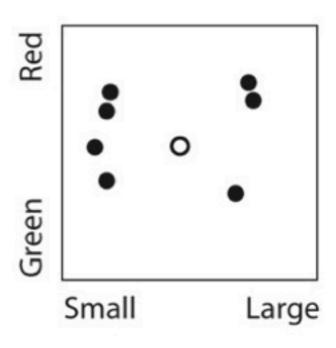




corresponding feature space







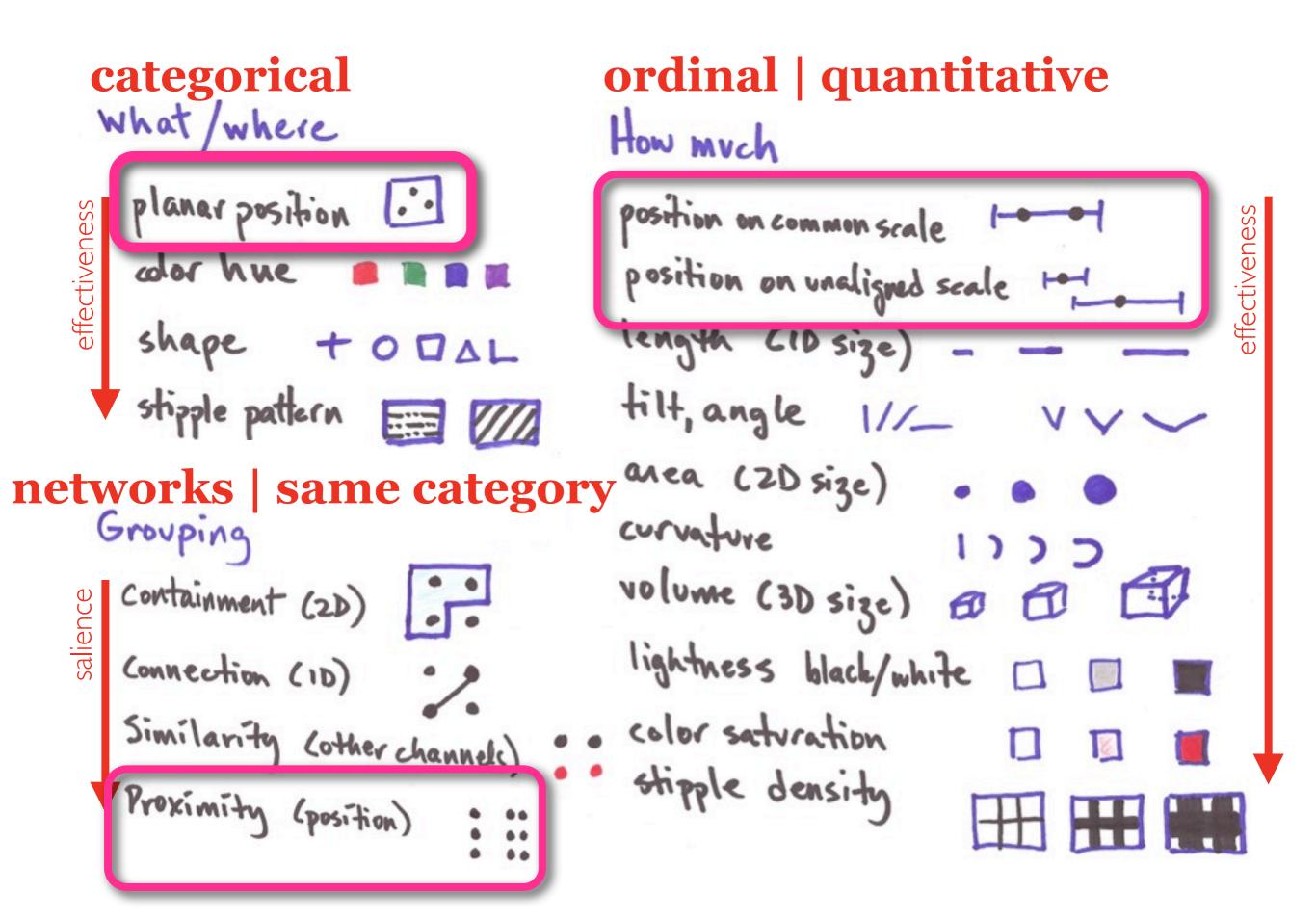
-relativity of perception

-marks and channels

-planar position

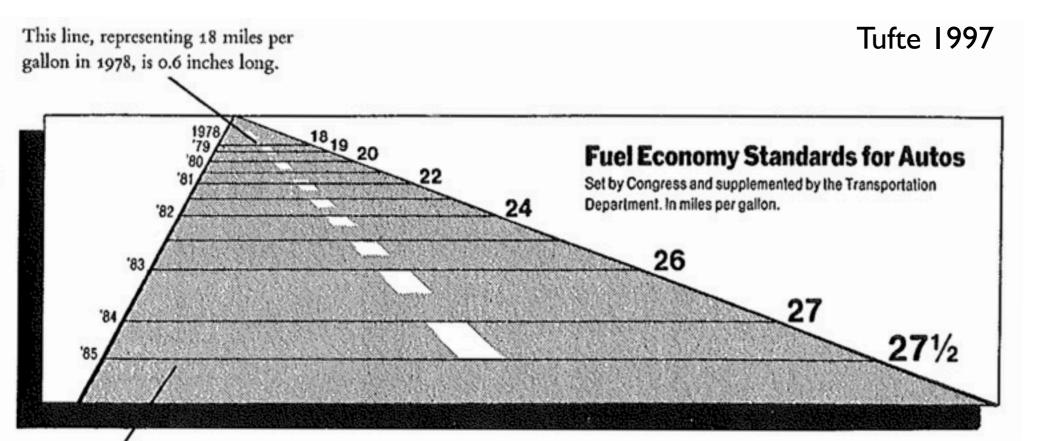
-color

WHAT'S SO SPECIAL ABOUT THE PLANE?

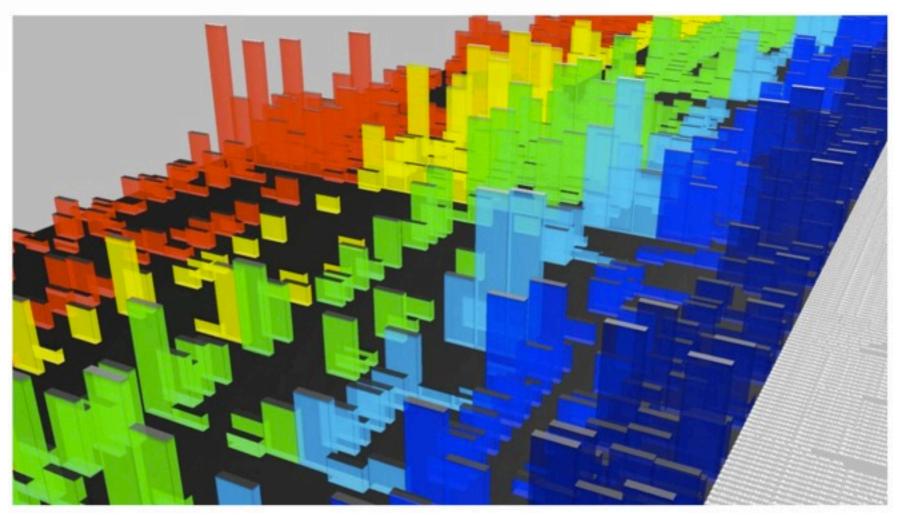


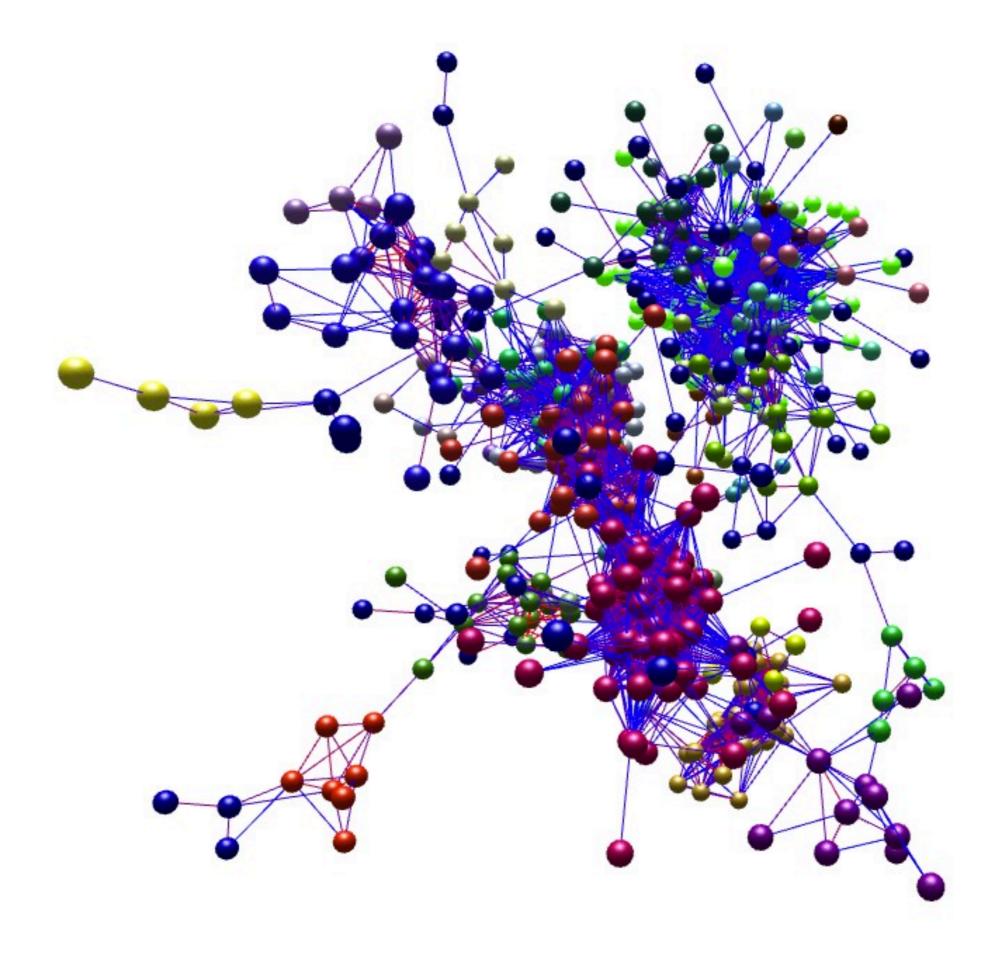
-power does not extend to 3D

- -perspective cues
 - interfere with color and size channels
- -occlusion of data

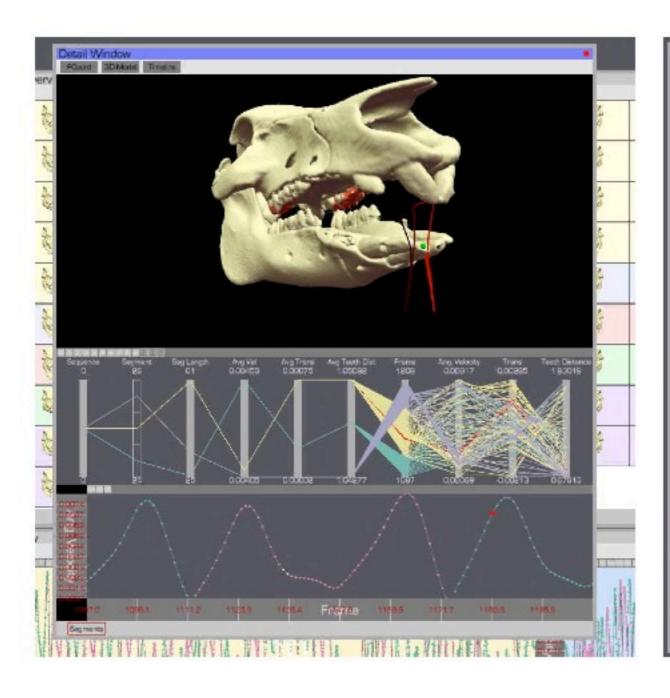


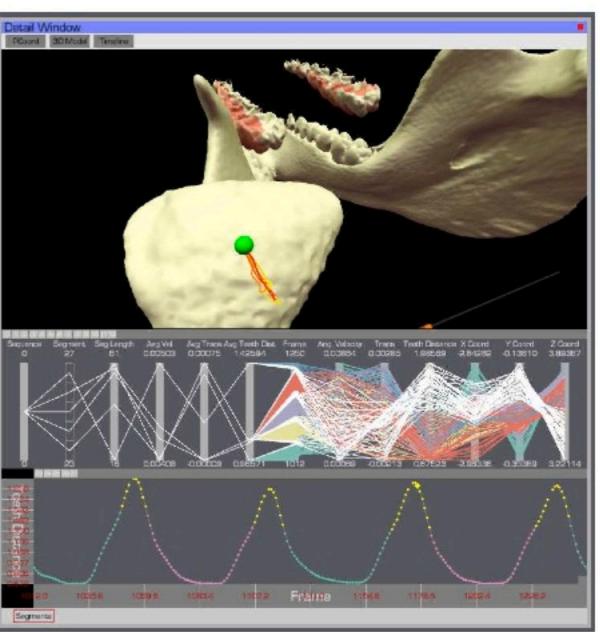
This line, representing 27.5 miles per gallon in 1985, is 5.3 inches long.





2D and 3D?





-relativity of perception

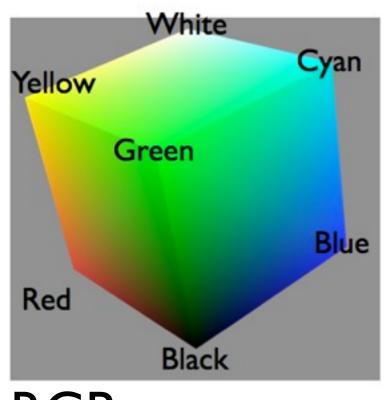
-marks and channels

-planar position

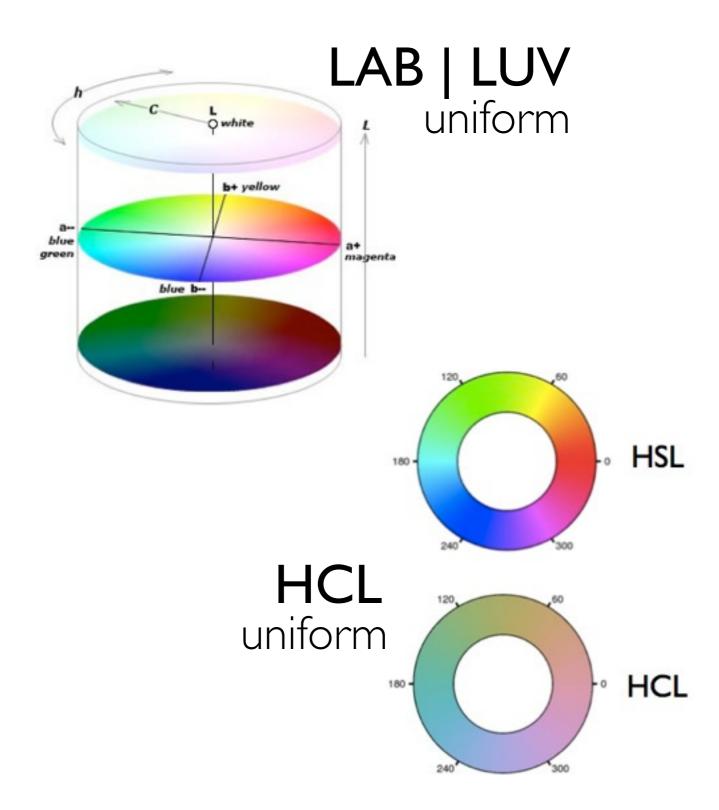
-color

WHY IS COLOR SO HARD TO USE?

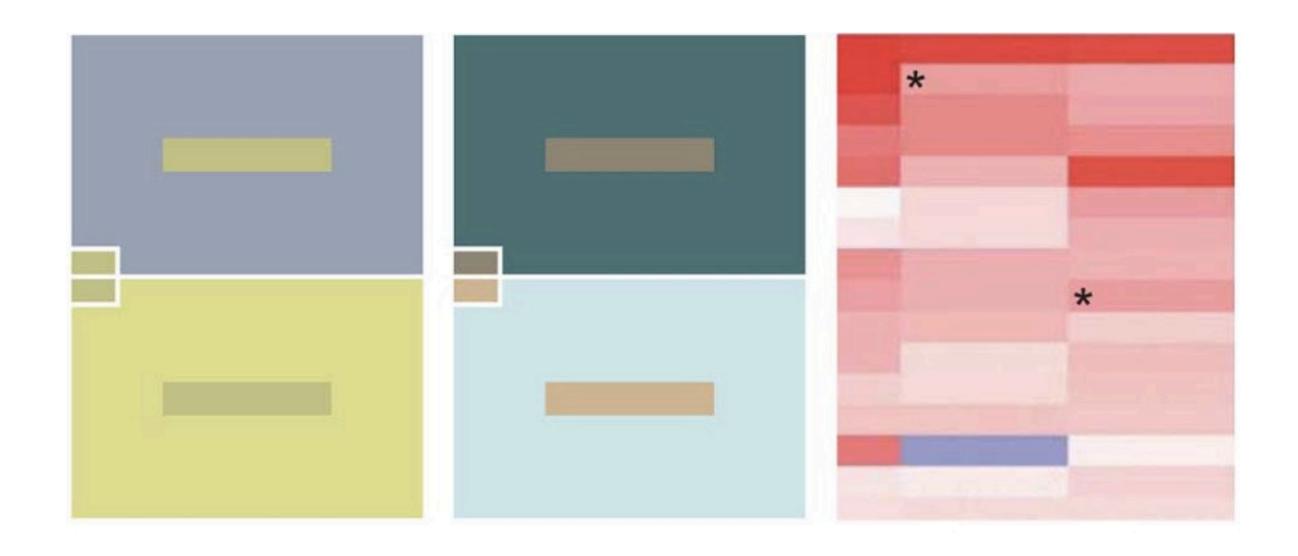
obtaining a perceptually uniform color space is challenging



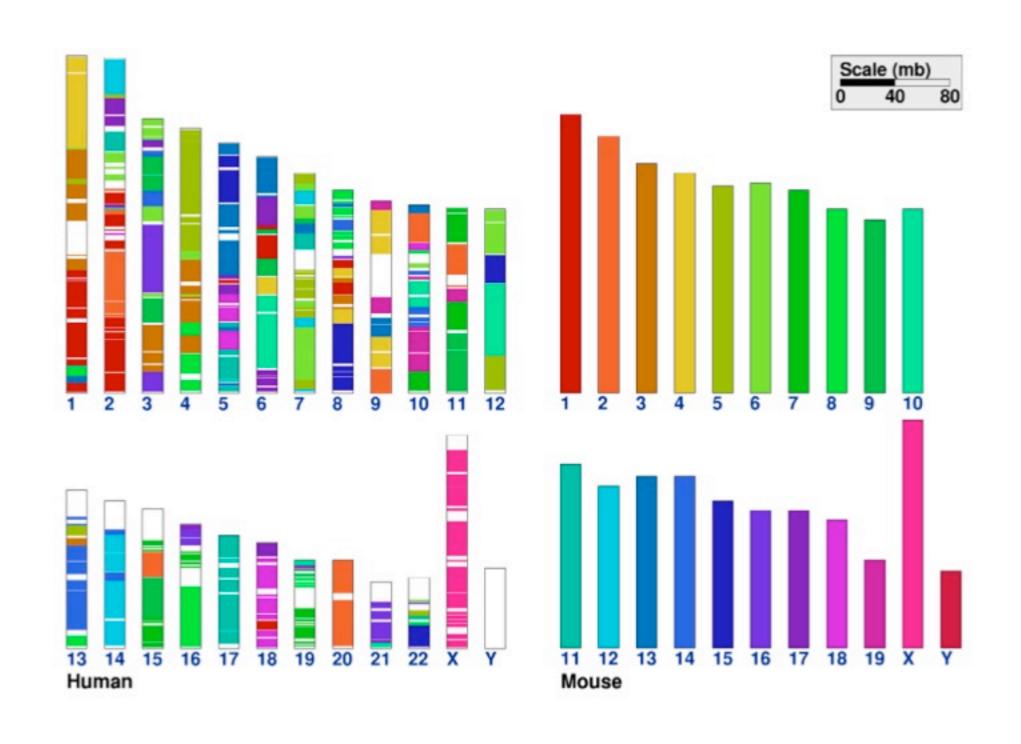




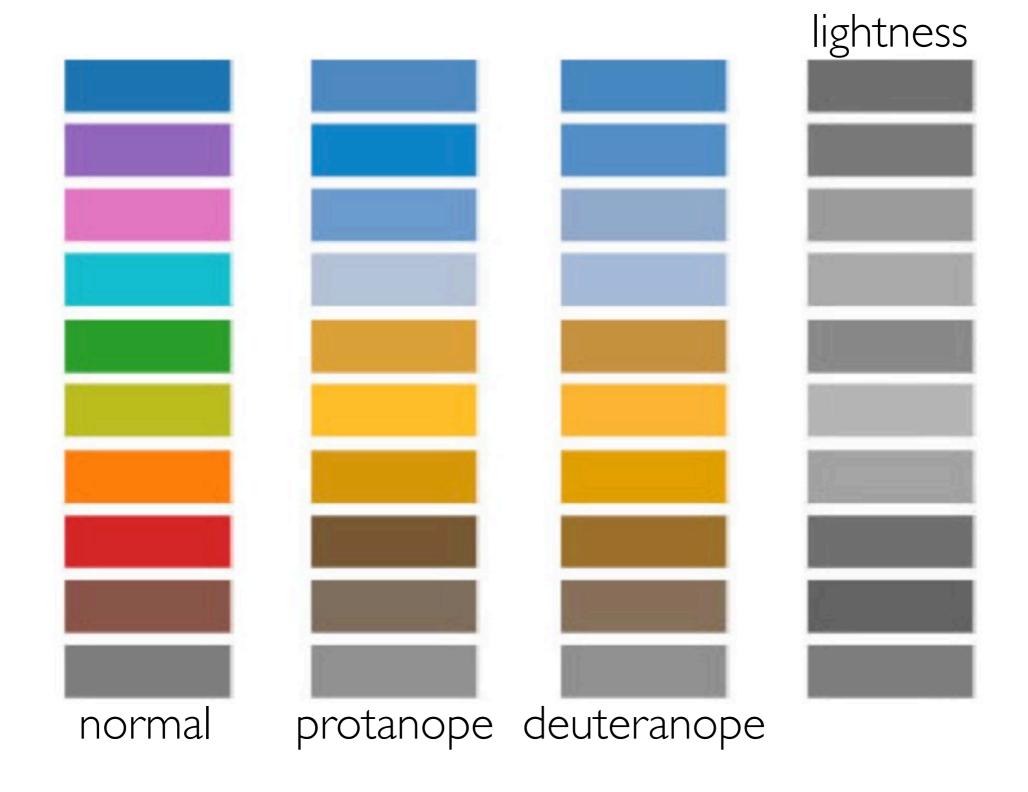
color interactions



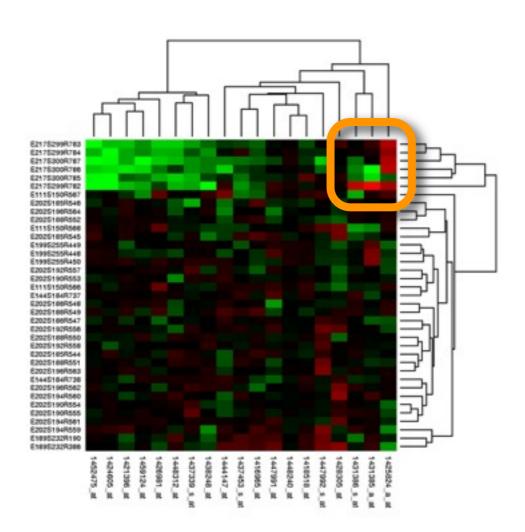
color discriminability

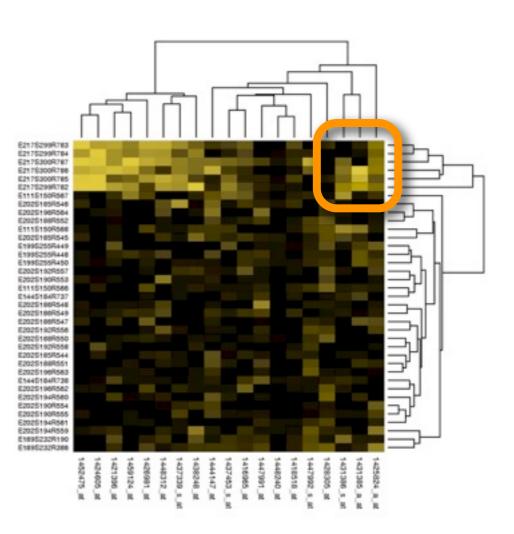


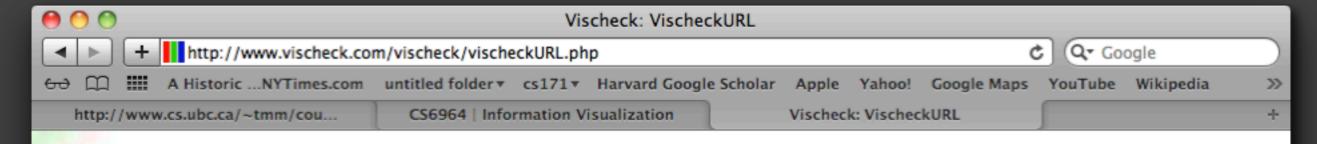
color blindness



color blindness











Home

Vischeck

- Run Images
- ·Run Webpages

Daltonize

Examples

Downloads

Info & Links

FAQ

About Us

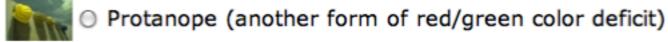
User quotes:

Just a note of thanks for providing an excellent site (or maybe that should be sight!). As a human-computer interaction educator, I've tried to tell students about these issues for years, with little success because of a lack of useful simulations, Your site will become a standard assignment for my course from now on. I also happen to be colorblind (red/green).

Try Vischeck on a Webpage

Select the type of color vision to simulate:

 Deuteranope (a form of red/green color defi





Enter the URL of any webpage- eg. www.google.com.

URL:	Run Vischeck!
0.12	Train riseneen.

Notes:

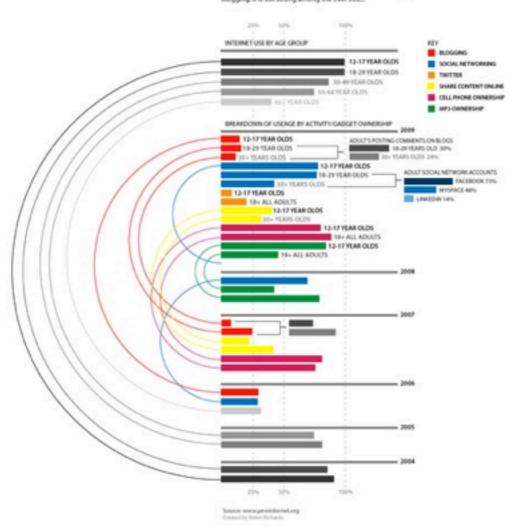
- Vischeck URL is still under development. We know that it will fail on many websites. For example, it won't work with sites that do an immediate redirect, use Macromedia Flash, or use certain javascript operations. Frames may also cause problems, but you can run each frame separately to get around this.
- Style sheets are crudely supported but beware that many variants will give
 incorrect results. We are working on a new version to fix many of these issues.



How different age groups are using the internet

With the growth of social media networks such as Facebook and Twitter, traditional blogging has been usurped by micro-blogging quick and short 140 character updates instead of lengthy, in-depth (and sometimes still equally pointless) articles.

However, while teens and young adults seem to be shunning blogging, it is still strong among the over 30s...

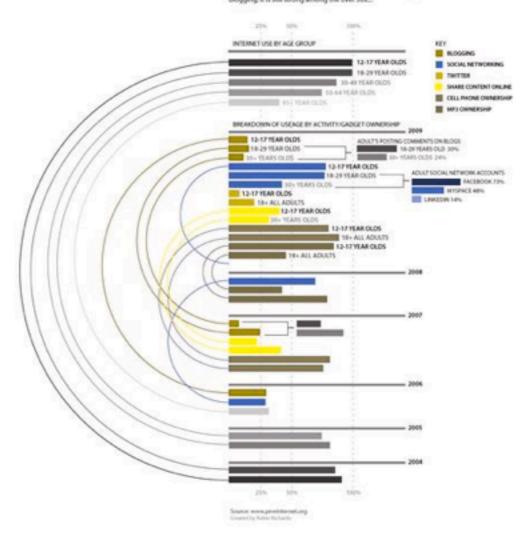




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However, while teems and young adults seem to be shunning blogging, it is still strong among the over 30s...



Visualization Viewpoints

Editor: Theresa-Marie Rhyne

Rainbow Color Map (Still) Considered Harmful

David Borland and Russell M. Taylor II University of North Carolina at Chapel Hill Research has shown that the rainbow color map is rarely the optimal choice when displaying data with a pseudocolor map. The rainbow color map confuses viewers through its lack of perceptual ordering, obscures data through its uncontrolled luminance variation, and actively misleads interpretation through the introduction of non-data-dependent gradients.

Despite much published research on its deficiencies, the rainbow color map is prevalent in the visualization community. We present survey results showing that the rainbow color map continues to appear in more than half of the relevant papers in IEEE Visualization mercials, weather forecasts, and even the IEEE Visualization Conference 2006 call for papers, just to name a few. The problem with this wide use of the rainbow color map is that research shows that it is rarely, if ever, the optimal color map for a given visualization. ¹⁻⁶ Here we will discuss the rainbow color map's characteristics of confusing the viewer, obscuring data, and actively misleading interpretation.

Confusing

For all tasks that involve comparing relative values, the color map used should exhibit perceptual ordering.

Conference proceedings: for example, it appeared on the ReE CO MMEEN iDIE TO THE PROPERTY OF T

toolkits that we inspected. The visualization community must do better.

In this article, we reiterate the characteristics that make the rainbow color map a poor choice, provide examples that clearly illustrate these deficiencies even on simple data sets, and recommend better color maps for several categories of display.

The goal is to make the rainbow color map as rare in

values mapped to darker shades of gray are lower in value than values mapped to lighter shades of gray. This mapping is natural and intuitive.

The rainbow color map is certainly ordered—from a shorter to longer wavelength of light (or vice versa)—but it's not perceptually ordered. If people are given a series of gray paint chips and asked to put them in order, they will consistently place them in either a dark-to-light

How NOT to Lie with Visualization

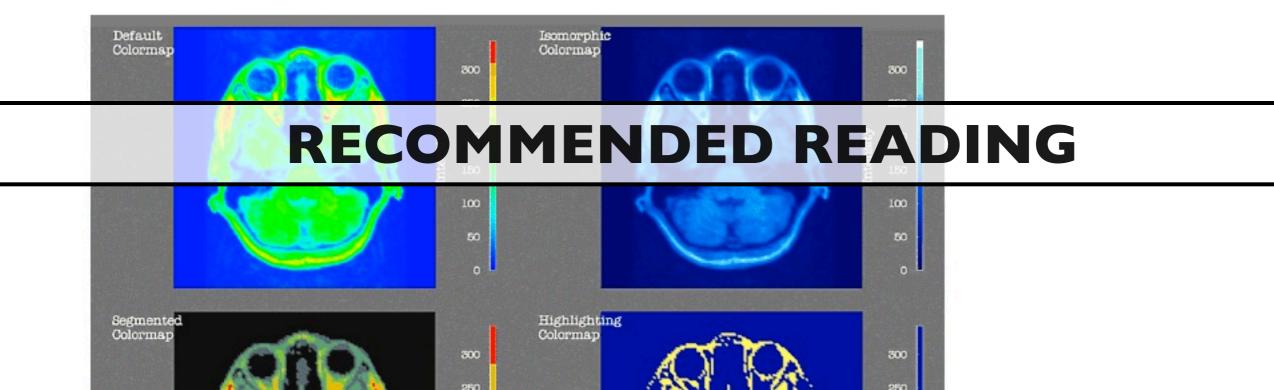
Bernice E. Rogowitz rogowtz@watson.ibm.com

Lloyd A. Treinish 1loydt@watson.ibm.com

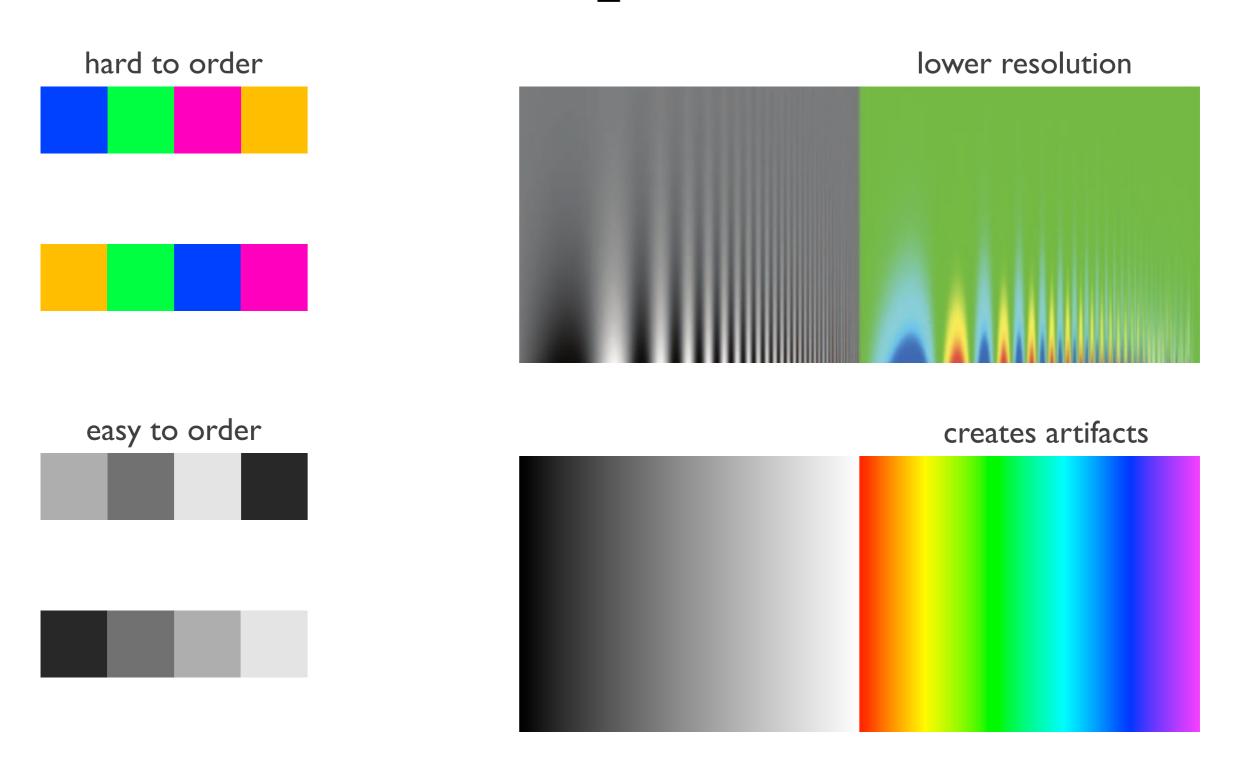
IBM Thomas J. Watson Research Center Yorktown Heights, NY

Introduction

How data are represented visually has a powerful effect on how the structure in those data is perceived. For example, in Figure 1, four representations of an MRI scan of a human head are shown. The only difference between these images is the mapping of color to data values, yet, the four representations look very different. Furthermore, the inferences an analyst would draw from these representations would vary considerably. That is, variations in the method of representing the data can significantly influence the user's perception and interpretation of the data.

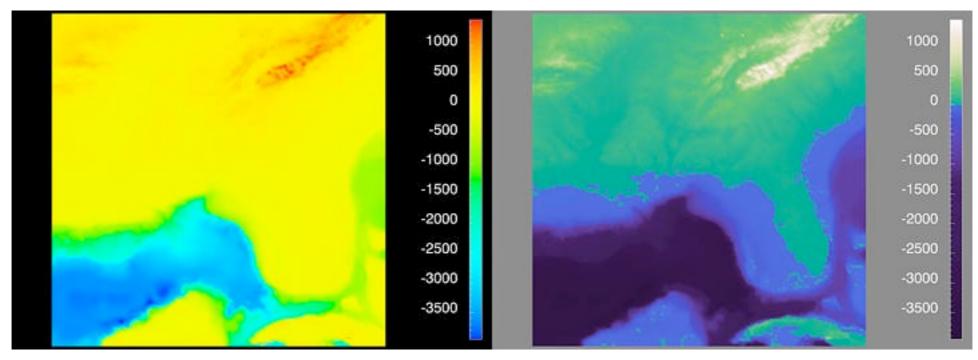


rainbow colormaps



rainbow colormaps

Southeastern United States and Gulf of Mexico



zero crossing not explicit

HELP!

Get it right in black and white. Maureen Stone

-hue: categorical



-luminance: ordinal and quantitative

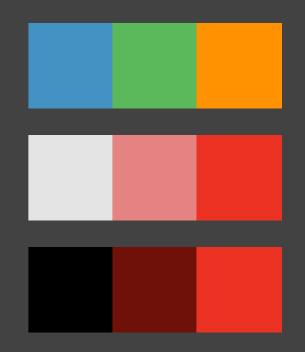
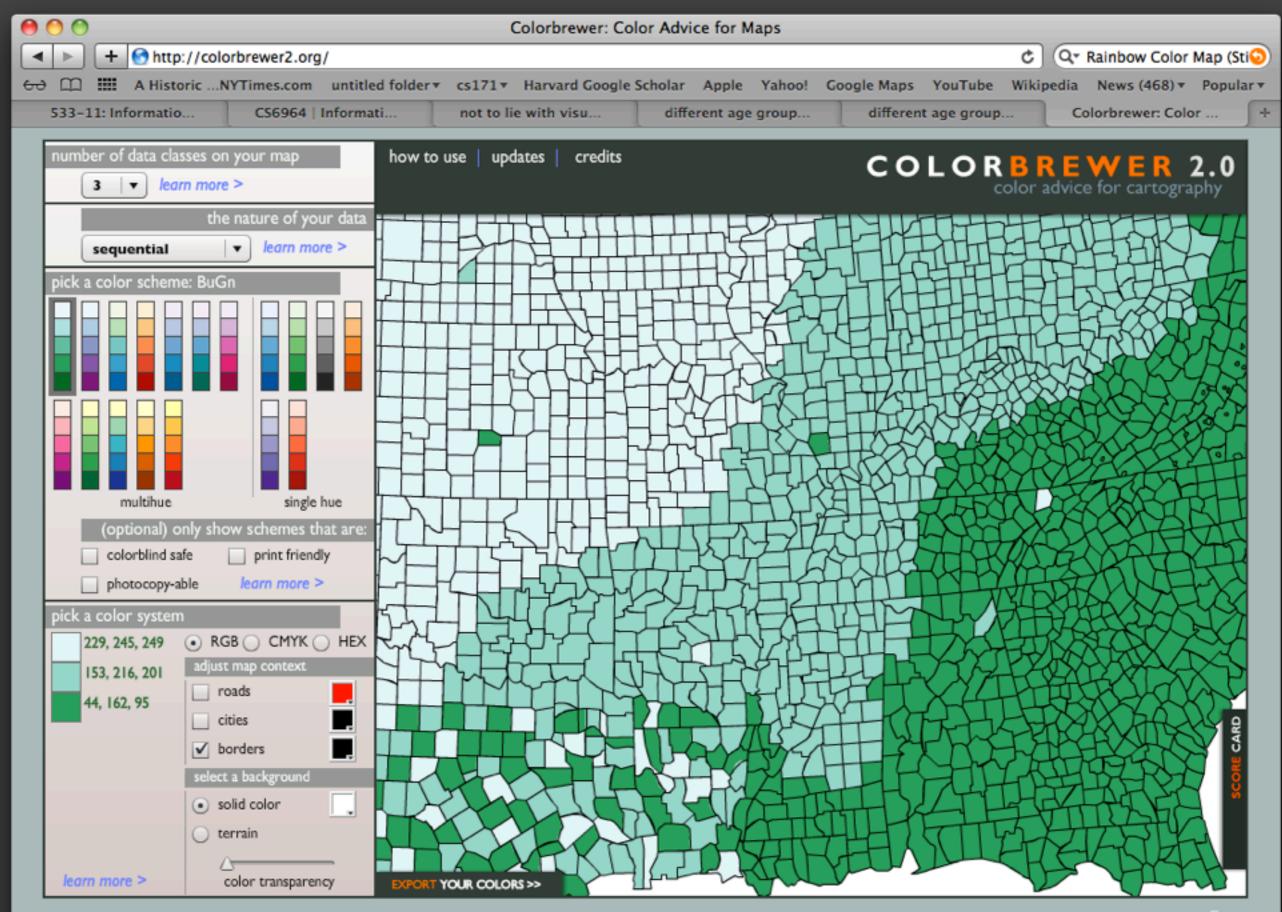


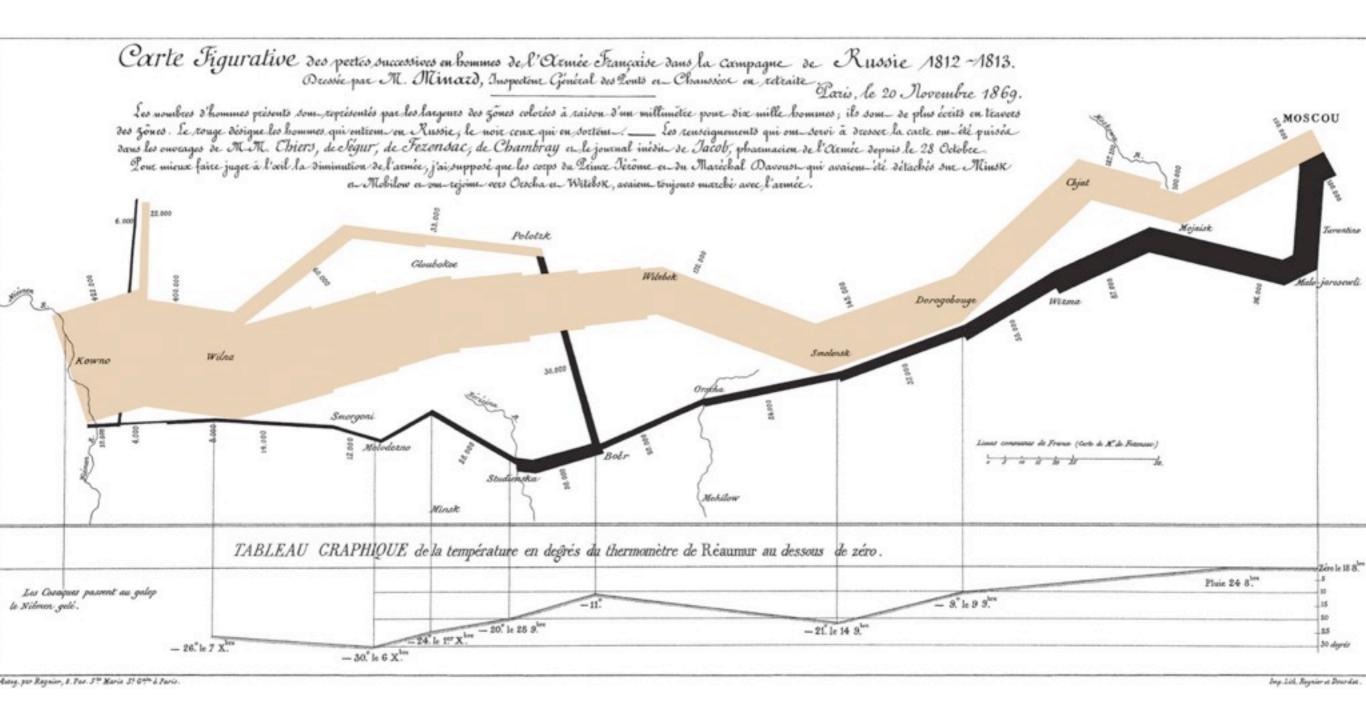
TABLEAU COLORS







encoding exercise ...



L6: Tasks and Interaction

REQUIRED READING

Interaction Principles

Several principles of interaction are important when designing a visualization: classes of change, latency and feedback, the costs of interactivity, and spatial cognition. Two slogans summarize sets of tradeoffs: one is eyes over memory, and another is resolution and integration over immersion.

4.1 Classes of Change

The fundamental point of interactivity is that the display is dynamic rather than static; that is, things change. We can categorize the kind of change that occurs in a display into four major types: a change of selection that triggers a different highlighting of dataset elements, a change of viewport that arises from navigating, a change of spatial ordering of the elements from sorting, and a change of the entire visual encoding.

4.1.1 Changing Selection

Selecting items is a fundamental piece of the interaction vocabulary. Many

The Eyes Have It: A Task by Data Type Taxonomy for Information Visualizations

Ben Shneiderman
Department of Computer Science,
Human-Computer Interaction Laboratory, and Institute for Systems Research
University of Maryland
College Park, Maryland 20742 USA
ben@cs.umd.edu

Abstract: A useful starting point for designing advanced graphical user interfaces is the Visual Information-Seeking Mantra: Overview first, zoom and filter, then details-on-demand. But this is only a starting point in trying to understand the rich and varied set of information visualizations that have been proposed in recent years. This paper offers a task by data type taxonomy with seven data types (1-, 2-, 3-dimensional data, temporal and multi-dimensional data, and tree and network data) and seven tasks (overview, zoom, filter, details-on-demand, relate, history, and extract).

Everything points to the conclusion that the phrase 'the language of art' is more than a loose metaphor, that even to describe the visible world in images we need a developed system of schemata.

E. H. Gombrich Art and Illusion, 1959 (p. 76)

1. Introduction

Information exploration should be a joyous

understood information need (known-item search) to developing an understanding of unexpected patterns within the collection (browse) (Marchionini, 1995).

Exploring information collections becomes increasingly difficult as the volume grows. A page of information is easy to explore, but when the information becomes the size of a book, or library, or even larger, it may be difficult to locate known items or to browse to gain an overview.

Designers are just discovering how to use the rapid and high resolution color displays to present large amounts of information in orderly and user-controlled ways. Perceptual psychologists, statisticians, and graphic designers (Bertin, 1983; Cleveland, 1993; Tufte, 1983, 1990) offer valuable guidance about presenting static information, but the opportunity for dynamic displays takes user interface designers well beyond current wisdom.

2. Visual Information Seeking Mantra

The success of direct-manipulation interfaces is indicative of the power of using computers in a more visual or graphic manner. A picture is often cited to be worth a thousand words and, for some (but not all)

Low-Level Components of Analytic Activity in Information Visualization

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ABSTRACT

Existing system-level taxonomies of visualization tasks are geared more towards the design of particular representations than the facilitation of user analytic activity. We present a set of ten low-level analysis tasks that largely capture people's activities while employing information visualization tools for understanding data. To help develop these tasks, we collected nearly 200 sample questions from students about how they would analyze five particular data sets from different domains. The questions, while not being totally comprehensive, illustrated the sheer variety of analytic questions typically posed by users when employing information visualization systems. We hope that the presented set of tasks is useful for information visualization system designers as a kind of common substrate to discuss the relative analytic capabilities of the systems. Further, the tasks may provide a form of checklist for system designers.

CR Categories and Subject Descriptors: H.5.0 [Information Interfaces and Presentation]: General; J.0 [Computer Applications]: General

Additional Keywords: Analytic activity, taxonomy, knowledge discovery, design, evaluation.

1 INTRODUCTION

Information visualization research, especially that dealing with the automatic generation of information presentations [10,15], has produced several taxonomies of system tasks that map visualization operations to user cognitive processes. In one sense, these taxonomies might be considered low-level task taxonomies

With the aim of generating an actionable means for supporting analytic activity, we wish to rethink some of the lower-level task taxonomies that focus on a generated presentation as an end result. In general, information visualization can benefit from understanding the tasks that users accomplish while doing actual analytic activity. Such understanding achieves two goals: first, it aids designers in creating novel presentations that amplify users' analytic abilities; second, it provides a common vocabulary for evaluating the abilities and affordances of information visualization systems with respect to user tasks.

We argue that a stronger focus on user tasks and analytic activities in information visualization is necessary as current tools do not seem to support analytic activity consistently. A 2004 study by Saraiya and North found that insights generated from tools used to visualize gene expression data were not generally valuable according to domain experts [11]. Systems such as IN-SPIRE [7] support analytic activities within the domain of document search but may not generalize across domains. Current tools may not even support representational activity very well; consider, for example, the Kobsa study showing only 68-75% accuracy on relatively simple tasks during commercial tool evaluation [8].

1.2 The Nature of Analytic Activity

User analysis questions and tasks as part of analytic activity typically range from broader, "high-level" goals to much more specific, "low-level" inquiries. For example, a person studying the history of motion picture films may have "high-level", uncertainty-tinged knowledge goals such as understanding trends in popularity over time or determining how to predict which