Data Visualization (DSC 530/CIS 568)

Colormaps

Dr. David Koop
Color
Color
Light Reflection & Absorption
Color != Wavelength

But rather, a combination of wavelengths and energy

[via M. Meyer]
Human Color Perception

Metamerism: same three responses == same color

[via M. Meyer]
Opponent Process Theory

[Machado et. al, 2009]
Color Blindness

- **Normal**
- **Protanopia**
- **Deuteranopia**
- **Tritanopia**

[via M. Meyer]
Color Spaces and Gamuts

All colors visible to the average human eye are contained inside the diagram.

The colors along any line between two points can be made by mixing the colors at the end points. In this case Green + Red = Yellow.

The edge of the diagram, called the spectral locus, represents pure, monochromatic light measured by wavelength in nanometers. These are the most saturated colors.

The least saturated colors are at the center, emanating from white.

Color gamut: subset of colors that can be represented by mixing the colors at its corners.

“line of purples”: these colors are fully saturated but can only be made by mixing two colors (red and blue).

[Anatomy of a CIE Chromaticity Diagram]
Color Models

- A **color model** is a representation of color using some basis
- RGB uses three numbers (red, blue, green) to represent color
- Color space ~ color model, but there can be many color models used in the same color space (e.g. OGV)
- Hue-Saturation-Lightness (HSL) is more intuitive and useful
  - Hue captures pure colors
  - Saturation captures the amount of white mixed with the color
  - Lightness captures the amount of black mixed with a color
  - HSL color pickers are often circular
- Hue-Saturation-Value (HSV) is similar (swap black with gray for the final value), linearly related
Simultaneous Contrast
Simultaneous Contrast
Simultaneous Contrast
Assignment 3

• Due next Thursday (3/28)
• Geographic Visualization and Colormaps: D3 Map Example
• Uses data about affordable housing in Massachusetts
Projects

• Feedback soon
• Continue to work on designs
• Create multiple alternatives to visualize data
• Focus on visual encoding and interaction
Colormap

- A colormap specifies a mapping between colors and data values
- Colormap should follow the expressiveness principle
- Types of colormaps:

  **Binary**
  - y
  - n

  **Diverging**
  - -1
  - 0
  - +1

  **Categorical**
  - T
  - F
  - A

  **Sequential**
  - 3
  - 2
  - 1

[Munzner (ill. Maguire), 2014]
Categorical vs. Ordered

- Hue has no implicit ordering: use for categorical data
- Saturation and luminance do: use for ordered data

[Munzner (ill. Maguire), 2014]
Number of distinguishable colors?

[Sinha & Meller, 2007]
Number of distinguishable colors?

[Sinha & Meller, 2007]
Discriminability

• Often, fewer colors are better
• Don't let viewers combine colors because they can't tell the difference
• Make the combinations yourself
• Also, can use the "Other" category to reduce the number of colors
Ordered Colormaps

• Used for ordinal or quantitative attributes
• \([0, N]\): Sequential
• \([-N, 0, N]\): Diverging (has some meaningful midpoint)
• Can use hue, saturation, and luminance
• Remember hue is not a magnitude channel so be careful
• Can be continuous (smooth) or segmented (sharp boundaries)
  - Segmented matches with ordinal attributes
  - Can be used with quantitative data, too.
Continuous Colormap

US EPA Regional Oxidant Model -- Midwest Ozone (ppbv): June 26, 1987, 18:00

[Bergman et al., 1995]
Segmented Colormap

US EPA Regional Oxidant Model -- Midwest Ozone (ppbv): June 26, 1987, 18:00

[Segmented colormap image]

[Bergman et al., 1995]
Is continuous better than segmented?
Continuous

Fig. 1: Experimental stimuli for five binning conditions: A. Continuous, B. 10m binning, C. 20m binning, D. 30m binning, E. 40m binning

Abstract

The expressiveness principle for visualization design asserts that a visualization should encode all of the available data, and only the available data, implying that continuous data types should be visualized with a continuous encoding channel. And yet, in many domains binning continuous data is not only pervasive, but it is accepted as standard practice. Prior work provides no clear guidance for when encoding continuous data continuously is preferable to employing binning techniques or how this choice affects data interpretation and decision making. In this paper, we present a study aimed at better understanding the conditions in which the expressiveness principle can or should be violated for visualizing continuous data. We provided participants with visualizations employing either continuous or binned greyscale encodings of geospatial elevation data and compared participants' ability to complete a wide variety of tasks. For various tasks, the results indicate significant differences in decision making, confidence in responses, and task completion time between continuous and binned encodings of the data. In general, participants with continuous encodings were faster to complete many of the tasks, but never outperformed those with binned encodings, while performance accuracy with binned encodings was superior to continuous encodings in some tasks. These findings suggest that strict adherence to the expressiveness principle is not always advisable. We discuss both the implications and limitations of our results and outline various avenues for potential work needed to further improve guidelines for using continuous versus binned encodings for continuous data types.

Index Terms —Geographic/Geospatial Visualization, Qualitative Evaluation, Color Perception, Perceptual Cognition

INTRODUCTION

A foundational design principle in visualization is the expressiveness principle, which states that a visual encoding should express all of the relationships in the data, and only the relationships in the data. For a continuous data type, this implies that a continuous encoding channel is a good choice. In practice, however, domains such as cartography and meteorology have strong conventions that visualize continuous data with a discrete encoding. These domains rely on visual channels, such as color and saturation to encode a continuous function defined over two-dimensional space, known as a 2D scalar field. They commonly do so by employing discrete colormaps or contour lines, also called isarithmic maps.

Existing literature provides little guidance about encoding continuous, 2D scalar fields with binned colormaps, or how this design decision affects data interpretation and decision making. Research into properties of colormaps for encoding continuous data types has largely focused on continuous colormaps. This line of research provides guidance on how to capture properties of the data, such as divergence around a center point or emphasis on one end of the data range. These papers go so far as proposing corresponding binned colormaps, but do not make claims, or even discuss, their efficacy for continuous data. Work on transfer function design has also proposed methods for binning colors, but with a focus on volumetric scalar fields, with the underlying goal of classifying materials or features, as opposed to directly understanding the continuous nature of the data.
Evaluating the Impact of Binning 2D Scalar Fields

Lace Padilla, P. Samuel Quinan, Miriah Meyer, and Sarah H. Creem-Regehr

Abstract

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Fig. 1: Experimental stimuli for five binning conditions: A. Continuous, B. 10m binning, C. 20m binning, D. 30m binning, E. 40m binning.
Fewer Segments

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Types of Tasks

- Locate/Explore & Identify: Highest Point (Global, In Region), 275m
- Locate/Explore & Compare: Height Compare/Rank
- Explore & Identify: Steepest
- Lookup & Identify: Lookup
- Explore & Compare: Steepness Compare/Rank
- Browse & Summarize: Average Height
- Browse & Compare: Compare Average Height
- Combination: Steepest at 355m

[Padilla et al., 2017]
Results

- "[C]ontrary to the expressiveness principle, no cases were found in which a continuous encoding of 2D scalar field data was advantageous for task accuracy, and for some tasks, specific binned encodings facilitated accuracy."
- "[S]upport for the counterintuitive finding that decisions with binned encoding were slower than those made with continuous encoding"
- Word of caution: single image!

[Padilla et al., 2017]
Ordering Color?

- Actively misleading
- Not only does the rainbow color map confuse viewers through its lack of perceptual ordering and obscure data through its inability to present small details, but it actively misleads the viewer by introducing artifacts to the visualization.
- The rainbow color map appears as if it's separated into bands of almost constant hue, with sharp transitions between hues. Viewers perceive these sharp transitions as sharp transitions in the data, even when this is not the case.
- When combined with the lack of perceptual ordering, viewers face a daunting task when trying to correctly interpret the data via the rainbow color map.
- The goal of visualization is to present data so that viewers can quickly and accurately learn about the underlying data. The rainbow color map does a great deal to hinder this learning process by introducing confusing artifacts in some locations and reducing detail in others.

Prevalence of the rainbow color map

- Although researchers have well documented these deficiencies, the visualization community still widely uses the rainbow color map.
- We present the findings of two surveys illustrating this prevalence.
- IEEE Visualization proceedings
- We searched the IEEE Visualization conference proceedings from 2001 through 2005 for papers that displayed data using a pseudocolor map.
- We included visualizations in which the rainbow color map was applied to surfaces, such as isosurfaces and streamlines.
- We excluded volume renderings as the literature does not address the relative merits of the rainbow color map when used for a color transfer function (although it seems clear that the same objections would apply).
- We did not count visualizations that used a banded version of the rainbow color map because explicit banding can be a useful visualization technique.
- We only included scalar data visualizations, excluding techniques such as mapping vector components to RGB—which is common with diffusion tensor MRI images.
- Such visualizations can appear at first glance to use the rainbow color map, but they are in fact using a different technique (see Rheingans [8] for a discussion of the hazards of encoding multiple values into a pseudocolor map).

Results

Table 1 (next page) presents statistics from the 2001 through 2005 IEEE Visualization Conference proceedings. The table gives percentages of papers implementing pseudocoloring to display data using the rainbow color map. We've included all papers that include at least one use of the rainbow color map. The results are alarming:

- Each year between 40 and 59 percent of all papers using pseudocoloring used a rainbow color map.

[Borland & Taylor, 2007]
Rainbow Colormap

[Bergman et al., 1995]
Don't Use Rainbow Colormaps

Which has a discontinuity?

[M. Bussonnier]
Other Colormaps Work Better

Which has a discontinuity?

[M. Bussonnier]
Artifacts from Rainbow Colormaps

(Borland & Taylor, 2007)
Two-Hue Colormap

[Bergman et al., 1995]
Rainbow Colormap

Obama & Romney Tweets
(2012 Election)

[0 150+]

[A. C. Robinson, 2012]
Single-Hue Colormap

Obama & Romney Tweets (2012 Election)

[A. C. Robinson, 2012]
Isoluminant Rainbow Colormap

Original

Isoluminant

[Kindlmann et al., 2002]
D3's color scales

- [https://github.com/d3/d3-scale-chromatic](https://github.com/d3/d3-scale-chromatic)
- In v5, included in default bundle (no separate import)
- D3's built-in color scales
- Derived from ColorBrewer
- Sequential and diverging scales created using interpolation
- Hue can change, but be careful
- Color ramp [M. Bostock]
"Get It Right in Black and White" - M. Stone

Matlab jet colormap

[S. Eddins (Matlab Blog), 2014]
"Get It Right in Black and White" - M. Stone

Matlab jet colormap (B&W)

[S. Eddins (Matlab Blog), 2014]
"Get It Right in Black and White" - M. Stone

Matlab parula colormap

[S. Eddins (Matlab Blog), 2014]
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Bivariate Colormaps

Munzner (ill. Maguire), 2014

D. Koop, DSC 530, Spring 2019
Remember Separable vs. Integral
Remember Separable vs. Integral

The map at right is a product of overlaying the three sets of data. The variation in hue and value has been produced from the data shown above. In general, darker counties represent a more educated, better paid population while lighter areas represent communities with fewer graduates and lower incomes.
What about uncertain data?
Bivariante Colormap (Uncertainty → Saturation)

[Correll et al., 2018]
Value-Suppressing Uncertainty Palette (VSUP)

Same Channels, just binned differently

[Correll et al., 2018]
Bivariate Colormap (Uncertainty → Saturation)

[Correll et al., 2018]
Value-Suppressing Uncertainty Palette

[Correll et al., 2018]
Evaluation

- Tasks:
  - Identification: locate spatial regions
  - Prediction: place battleships in "safest locations"

[Correll et al., 2018]
Identification Results

Figure 6: The 8 conditions from the identification experiment. Juxtaposed maps require participants to make an error-prone connection between areas in two separate maps in order to make a decision that integrates value and uncertainty. Traditional bivariate maps integrate both value and uncertainty. VSUPs attempt to improve on traditional bivariate maps by reducing color resolution as uncertainty increases, discouraging conclusions based on noisy or imprecise data.

Figure 7: Accuracy results for the identification experiment. For examples of each condition, see Figure 6. Juxtaposing two univariate maps for both value and uncertainty requires an error-prone search task for identification tasks. Continuous rather than discrete bivariate maps requires an error-prone color encoding and estimation task. Discrete bivariate maps, both VSUPs and otherwise, avoid these issues. The confidence intervals are bootstrapped 95% CIs of trimmed means.

Bins \((M = 0.63, SD = 0.48)\) performed significantly better than charts with continuous color maps \((M = 0.47, SD = 0.5)\). The lack of quantization bias in continuous maps is countered by the perceptual error in precisely estimating value from color. Relying on a discrete set of output colors simplifies this task.

We performed a second ANOVA among the superimposed discrete charts to determine the effect of legend shape (wedge or square) and quantization scheme (VSUP or standard) on performance, with participant ID as a random factor. We did not find a significant effect for either the legend shape \((F(1, 70) = 0.04, p = 0.84)\) or the quantization scheme \((F(1, 70) = 1.4, p = 0.24)\).

Figure 8: The prediction task. The participant has a list of locations, and ought to place their ships on locations with low probability of attack, and high certainty in this probability. Ships above the heatmap have yet to be placed.

For the prediction task, we gave participants the rules of a game similar to Battleship. Greis et al. [18] employ these game-like experimental tasks to assess how different visual designs communicate uncertainty information, which can be abstract or complex, to the general audience. In our task, the participant and a (fictional) adversary have to place tokens representing ships on a \(5 \times 5\) spatial grid, with the expectation that certain squares will be hit by missiles. Players have to place all their tokens before continuing. The objective is to minimize the number of your own ships that are hit.

In our task, participants were given a map representing the predictions of missile strikes in each location on the grid. The value component was the ship's danger if placed on the square. The uncertainty component was the confidence in this prediction. Other studies of uncertainty representation, such as in Cox et al. [12], have used “prediction + prediction” [Correll et al., 2018].
We recruited 24 participants for this task: we selected this task in order to promote risk-averse behavior. We limited our study to only 4 types: square and wedge bivariate maps. To capture differences in this non-normal distribution, and to illustrate that framings in terms of gains or losses produce reliably different outcomes. In particular:

- **VSUP** users would avoid highly uncertain targets with low safety but high certainty, while participants had at least one “safe” square (low danger and high certainty).
- **Traditional Bivariate Maps** would encourage participants to ignore uncertainty information.
- A risky player would choose guesses that fell within each of the 25% uncertainty bins of the tokens to place than there were “safe and certain” locations.
- A more conservative guesser might eschew high-risk, high-danger strategies where to place bets.
Results & Conclusions

- Legend shape has no significant effect
- Some indication that people avoid high uncertainty with VSUPs
- Tradeoff is that people do choose targets with higher danger when using a VSUP
- VSUPs present uncertainty information *simultaneously* (superimposed) instead of juxtaposed
- VSUPs encode value and uncertainty via *discrete, quantized bins* instead of continuously

[Correll et al., 2018]