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TOPICS IN SCIENTIFIC VISUALIZATION

Color Perception, the Importance of Gray and Residuals, on a Choropleth Map

By Dan Carr

Note: This article is the third in the sequence on choropleth maps. The previous articles addressed smooths and legends, respectively. This article shows the residual map for the continuing example of white male colon cancer mortality rates. As will be discussed below, the residuals are of interest in the context of generating epidemiological hypotheses. Since the plot is in color I have chosen to begin the article with a discussion of color and color perception.

The color discussion below provides a physics-based description and comments on perception. Many aspects of color use are not covered such as distinguishing foreground from background, adding additional layers of information, creating perceptual groups, providing depth cues, achieving balance in terms of complementary colors, and highlighting in terms of complementary colors. Further, little is said about color systems. Readers wanting more information can refer to the newsletter article on color systems (Eddy 1990) and a host of additional resources such as Foley et al (1990), Durrett (1987), Friedhoff and Benzon (1989), Tufte (1990), and Mante (1972).

Color

A physics-based description of visible light yields an intensity versus wavelength curve over the spectrum of 400 to 700 nanometers. Figure 1 provides an example for one color. Light consists of photons with characteristic wavelengths and wavelength corresponds inversely with frequency and energy. A physics-based intensity (energy) measure for a specific wavelength counts the number of photons striking a given area in a given length of time and scales the count by the energy for that particular wavelength. The perception of color is based on a weighted visual response to the intensity curve. Common descriptions refer to three different weightings, one for each of the three basic photon responsive components of the eye: rods, green cones and red cones. The construction of a brightness measure, called luminance, proceeds by settling on a single luminous efficiency curve (see Figure 1) as being representative of the composite visual response. The integrated product of the intensity function with the efficiency curve (or weighting function) produces a measure with units such as foot lumens. This measure is a rough approximation to perceived brightness.

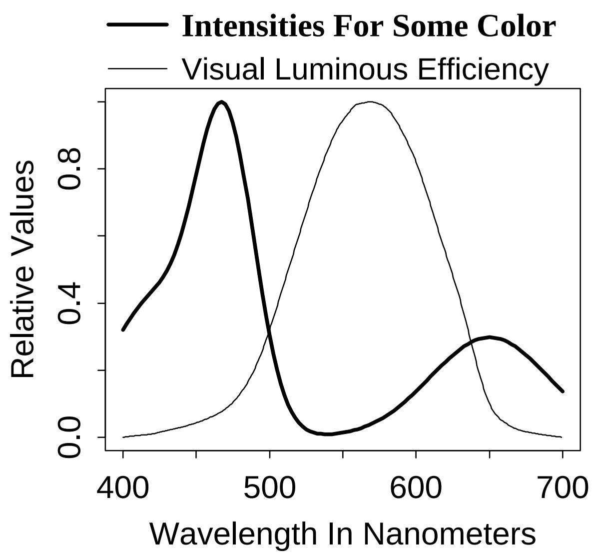

Figure 1. Intensity and Luminance Curves.

Many different intensity curves produce the same perceived color. Such colors are called monomers. Descriptive systems for characterizing perceptually discriminable colors typically involve three facets or dimensions. The HLS system describes color using the concepts of hue, lightness and saturation.

For monochromatic light, hue corresponds directly to the wavelength of the light. For example wavelengths of 470, 490, and 572 nanometers correspond to what is generally perceived to be pure blue, green and yellow, respectively. Most light that we see is not monochromatic but rather is composed of wavelength mixtures over regions of the visible spectrum. The hue of a mixture can be found by perceptually matching the color with mixtures of a monochromatic light and achromatic light. The monochromatic light in the match gives the hue. Hue is conveniently thought of as the dominant wavelength of a color. However in some cases the color actually has zero intensity for that particular wavelength. For example the combination of monochromatic red and green light does not contain yellow but appears yellow because photons with those two wavelengths jointly stimulate the red and green cones in the eye in a fashion similar to that of yellow light photons. Multidimensional scaling of judgements concerning hue closeness places hues on a “C” shaped curve in a plane (Shepard and Carroll 1966). The HLS descriptive system orders hues around a circle. Consequently hues are not good for representing values of an ordered variable.

A second aspect of color, saturation, refers to excitation purity. Monochromatic light appears fully saturated in color (provided the photon rate is high enough). Light containing a mixture of different wavelengths appears less saturated. Sunlight and other mixtures that are of roughly uniform intensity across the visible spectrum appear as totally unsaturated or achromatic. Saturation can be thought of as an ordered scale that involves a mixture of a pure chromatic color (such as red) and an achromatic color (such as some shade of gray). Representing an ordered variable using saturation is reasonable. The main limitation is that humans cannot discriminate many levels of saturation.

When the wavelength specific intensities are roughly the same across the visible spectrum, the color is perceived as being achromatic. Achromatic light can be thought of as gray levels from white through black. We perceive the mixtures produced by the sun and many electric bulbs as white light. We perceive surfaces reflecting white light equally across the visible spectrum as white when the reflectance is above 80% A surface reflecting 3% or less light appears to be black (Murch 1987). We perceive intermediate reflectances as levels of gray. In printing, the half-toning process produces grey-levels by putting patterns of black ink on white paper to reduce the reflectance. For CRT displays, “equal” mixtures of red, green and blue light emitted by the CRT phosphors produce gray. The apparent gray-level from white to black, depends on the intensity of the light from the three phosphors and the surrounding brightness.

Different authors refer to the notion of composite light intensity (or intensity contrast) using such words as brightness, lightness, and value. Whatever the word chosen, humans are very responsive to the intensity dimension of light. Humans can discriminate many levels of brightness, so brightness is the best color dimension for representing an ordered variable. The use of gray-levels is particularly convenient since it provides a brightness dimension without the risk of suggesting other competing orderings based on hue and saturation.

The above physics-based description of brightness follows that of Foley et al (1990). However, luminance as a measure of brightness does not tell the whole story. Murch (1987) uses the word brightness to refer to perceptual color changes that are a function of light intensity or roughly speaking, photon rates. As intensity increases it first becomes possible to see something, then it becomes possible to see dark unsaturated colors, next it is possible to see more and more saturated colors, and eventually it is possible to see saturated reds and yellows. At greater extremes of light intensity, the hues appear more desaturated and the colors can appear dazzling. A further phenomena is the apparent change in hue that accompanies a change in luminance. This is known as the Bezold-Brucke Effect and can necessitate some adjustments except at the three pure colors indicated above.

In controlled settings, colors can be ordered in terms of saturation and brightness but commonly encountered situations are much more complicated because color perception is relative. Our eye-brain systems diminish in response to steady state stimulation. When a small colored disk is surrounded by an annulus of a different color, adaptation (or diminished response) to the annulus color shifts the apparent color of the small disk toward the complementary color of the annulus. (Complementary colors in an additive light model are color pairs that produce white light.) If the annulus is green, the visual response to the green rapidly diminishes both for the annulus and the disk. For the disk, this adaptation produces a perceptual shift toward magenta. Land (see Friedhoff and Benzon 1991) discovered that he could produce richly colored images using two lights sources, such as white and red. He produced two gray-level slides using red and green filters. He then projected red light through the red filter slide and white light through the green filter slide. The result was not pink as in pigment mixing but a full color image with the color of regions relatively low in red saturation being shifted toward cyan. Apparent gray levels also relative. A brighter surround makes the inner disk appear darker. The relativity of color perception can complicate interpretation when color represents an ordered variable in choropleth maps and other varying-local-background applications.

Visual Subchannels

According to Friedhoff and Benzon (1991), visual processing involves separate pathways or channels that emphasize different facets of a scene. Their description gives three channels, a color channel that does not see the objects in great detail, a channel associated with movement and binocular depth information, and a channel that carries high-resolution information about shapes. The high-resolution shape channel processes changes in value (or brightness). This shape channel also carries much of the monocular information about depth.

Readers can perform a simple experiment to gain insight into the importance of brightness contrast in monocular depth perception. Start with a perspective view such that in Figure 2. Then make a similar image using a background color such as green and lines in another color such as red. Modify the intensities until the colors are brightness matched. In other words the lines should be as difficult as possible to see. Then observe how flat the image appears compared to the black and white version.

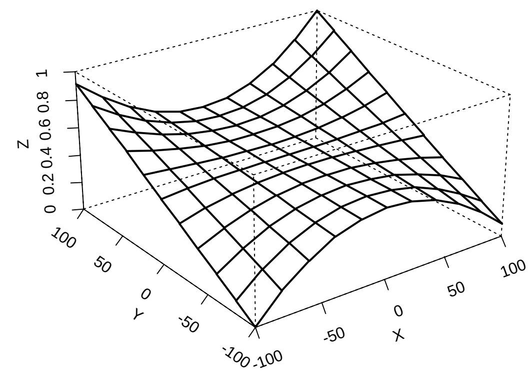

Figure 2. A simple pserspective plot.

Many scientific images use a spectral color order (red, orange, yellow, green, blue, violet) to represent an ordered variable. This can produce unintended visual effects because the colors are not ordered in brightness. The shape-channel picks out edges between colors of contrasting brightness and extracts monocular depth information based on local brightness comparisons. While purposeful jumps in brightness may emphasize selected contours and create perceptual groups that are relatively close in brightness, all to often people make color selections without regard to the shape and depth information that the color selection generates.

A gray-level plot can be used as a rough consistency check for a plot that uses color to encode an ordered variable. When colors have been encoded as RGB values and the RGB values are based on the standard NTSC phosphors, the Y component of the YIQ transformation, Y= .299R+.587G+.114B (see Eddy 1990) corresponds to luminance. This Y value can be equated to gray-level for production of the plot on a CRT display or on paper. (The paper version can have much better spatial resolution but may not be as effective because of halftone edge problems.) If the gray-level version appears inconsistent with the intended message, then the color selection should be reconsidered.

Controlling Contrast Noise

Tufte's (1990) description of laying and separation provides an introduction the elegant use of color. In his description, wild local variations in brightness (value) appear as noise. This phenomena is likely to occur in a choropleth map that represents residuals from spatial smooths. Figure 3 addresses the noise problem by plotting HSAs in gray when their residuals are small in absolute value. (See Carr and Pickle (1993) and Carr (1993) for details concerning the data and smoothing.) The legend in the noisy residual plot (not shown) prior to Figure 3, gave approximate values for the 5th and 95th population-based percentiles. The class interval from -3 to 3 is a convenient, symmetric rounding of those percentiles. The values of -8 and 8 were chosen heuristically based on the residual extrema. The double-ended color scale with darker saturated colors at the extremes is consistent with the separate representation of positive and negative residuals. This color scheme uses saturated color sparingly in accordance with Tufte's advice.

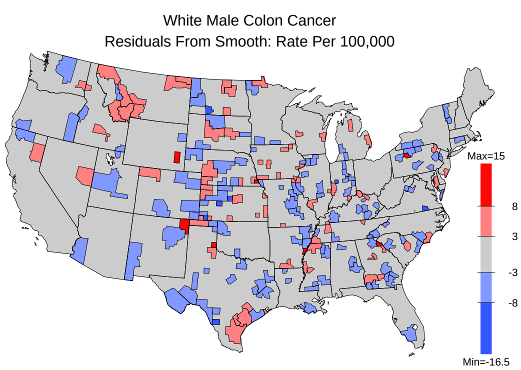

Figure 3. Residuals from a smooth fit.

Hypothesis Generation

Plotting residuals from spatial smooths of mortality rates is a useful device for generating epidemiological hypotheses. Knowing the location of a large mortality rate residual triggers the mental search for possible cancer related variables that are also unusual for the location. A match with locally unusual values provides a hypothesis for investigation. The failure to find a match among the immediately known variables suggests checking on additional variables. More generally, spatial smoothing provides a surrogate adjustment for cancer related variables that vary smoothly over space. The residuals can call attention to cancer related variables that do not vary smoothly over space.

In the residual plot, the red HSA in eastern Nebraska comes as no surprise to epidemiologists. In past decades epidemiologists noticed high rates in eastern Nebraska compared to other midwest rates. Further study found that the rates were associated with people of Czechoslovakian background and their dietary patterns (see Pickle et al 1987). Based on viewing cancer mortality maps for the three previous decades, it is possible that the other dark red HSAs in Figure 3 have not yet been studied as having locally high colon cancer rates. In Pennsylvania, the red HSA draws additional attention because of the light blue (low) neighboring HSA rates. Readers having hypotheses about any of the dark red regions are encouraged to send them to me. The clusters of light red HSAs in Montana and Texas are roughly consistent with the three decade trend map shown in Pickle et al 1987. However most of the other significant trend regions do not appear in this residual plot. The Montana cluster is evident in the 1970-1979 map but the Texas cluster is new. The dark blue HSAs and the light blue clusters can also be consider for possible associations.

Cautious Interpretation

Interpretation of this residual plot should proceed cautiously for several reasons. Unexplained variability remains. The smoothing fraction may be too large and the use of Poisson-based weights needs to be reviewed. The large residuals call for robust residual weights. In general smoothing methods are suspect at map edges and most methods are not designed to track discontinuities, should they be present in the data. In addition, the use of class intervals can hide important detail. As examples of this, the apparent Texas cluster is the result of smoothing two locally high HSA rates and the single dark red Nebraska HSA is not the only high rate HSA in the area. Smoothing methods accomplish their purpose when the examination of the smooth and residuals helps the analyst focus attention. The results are not to be interpreted in isolation from data, diagnostics and related knowledge.

The data are available and readers are encouraged to produce their own smoothed plots.

The impact of inverse variance weights should be considered in the interpretation of ordinary residuals. For example, Long Island has a large population and correspondingly the mortality rate has a small variance estimate. The inverse variance weight is relatively large, so the Long Island rate strongly influences its own smooth estimate and the estimates for the neighboring HSAs. This is evident if one examines the maps in the two previous articles. Seeing a large residual for Long Island would be a surprise. The anticipated result is that extreme residuals will tend to belong to small population HSAs. With a Poisson model for the number of deaths, the small population rates are more variable and the

HSA's exert less pull on the local smooth. Clusters of small population HSAs with extreme residuals are not particularly surprising. Since counties have been aggregated into HSAs to reduce the population size imbalance among analysis units, the situation is not as extreme as in county residual maps. Still, patterns in Figure 3 may be predominantly due to the "random variation" in small population HSA rates so plotting studentized residuals is an obvious next step.

Readers are encouraged to improve on the smoothing, to make their own choropleth residual maps, to generate their own hypotheses and reach their own conclusions. The data structures, modeling and plotting scripts, and postscript files are available by anonymous ftp to `galaxy.gmu.edu` under `submission/eda/maps`.

Acknowledgements

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UNIX COMPUTING

What is a Shell, Part Two

by Phil Spector

Note: This article is a continuation of the article appearing in the December, 1993 issue of this newsletter.

Job Control

The UNIX operating system accommodates the execution of programs in two modes: foreground mode, where the terminal or window being used does not prompt for a response until the program is completed; and background mode, which executes the program without tying up the terminal or window from which the command invoking the program was executed. By default, the commands you type are carried out in the foreground. In an environment with multiple windows, these distinctions are not so critical, since additional windows can be opened if the one in which a command was entered is not available.

Background commands are particularly useful in non-windowed environments.

When using a terminal with just one window, it can be very useful to run one or more commands in the background while an interactive session is being carried out. Even in a windowed environment, it can often be useful to run a program in the background if you know you will be logging off before the program has completed executing, since jobs in the foreground will terminate when you logoff. To make it known the the UNIX operating system that you wish to run a job in the background,