How Not to Lie with Visualization

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HOW *NOT* TO LIE WITH VISUALIZATION

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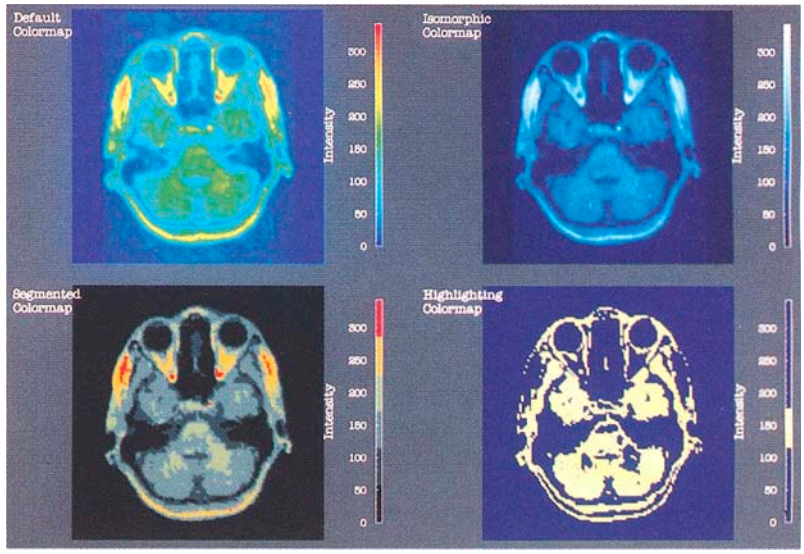

Figure 1. Choices in the representation of data can influence their interpretation. Here, four color maps have been applied to the same slice of an MRI scan of a human head. The resulting images convey different information.

How data are represented visually has a powerful effect on the perception and interpretation of the structure in those data. In Fig. 1, four representations of a magnetic-resonance-imaging (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.

The importance of visual representation has been a lively topic at the annual IEEE Computer Society Visualization conferences. This concept was first publicized by Huff in his book *How to Lie with Statistics*.[1] In this book and in the "How to Lie with Visualization" sessions at those conferences, the major concern is how the interpretation of data can be subverted by manipulating the data representation. In this article, we take a converse tack and ask: How can the interpretation of data be enhanced? To address this question, we consider the structure of the data, the perception of the visual dimensions used in visualization, and the task the analyst is trying to solve. We illustrate our discussion with examples drawn from a variety of color-mapping schemes.

The complexity of data mapping

Modern interactive systems give the user free rein over the mapping of data onto visual dimensions, and the number of visual dimensions available for data representation is exploding. A visualization can use x, y, and z to represent the spatial dimensions of an object, color can be mapped onto a surface representing a fourth dimension, the surface can be deformed according to a fifth, isocontour lines can represent a sixth, coloring them can represent a seventh, and glyphs on the surface can represent a few more dimensions, not to mention animation, transparency, and stereo. This great flexibility, however, can open a Pandora's box of problems for the user and easily give rise to visual representations that do not adequately reveal the structure in the data or that introduce misleading visual artifacts.

The appropriate use of color is an area of particular consternation. This is partly because the perceptual impact of a color cannot be reliably predicted from a knowledge of the red, green, and blue components generally made available to users. Furthermore, even if the three perceptual dimensions of color are surfaced to the users, they may not be aware that different aspects of the color signal communicate different characteristics of the data. Without guidance about the physical or psychophysical properties of color, or about which color maps are most appropriate for which types of data, the user is at a loss, even if the system provides a color-map editor or a library of precomputed color maps.

One common way developers of visualization software address this problem is to provide users with a default color map. The most common default color map, shown in the top left panel of Fig. 1, maps the lowest value in the variable to blue and the highest value to red and interpolates in color space (red, green, blue) to produce a color scale. This rainbow-hue color map is widely used in visualization but pro-

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duces several well-documented artifacts.[2-4] In this MRI image, for example, the color map creates perceived contours that do not reflect discrete transitions in the data, structures in the data that fall within one of these artificial bands are not represented, and attention is drawn to the yellow areas because they are the brightest, not because they are in any way the most important.

Helping users to avoid inaccurate and ineffective representations of their data, furthermore, is not confined to offering a selection of color maps. Confusion also arises in the application of contours, transparency, depth, and animation, especially since the perception of one attribute can affect the perception of another. For example, if a blue and a red object are placed behind a translucent green object, observers might expect that both objects would maintain their color but be tinged by the color of the transparent layer. This is true for the blue object, which appears bluish-green, but not for the red object, which appears yellow. This effect is well understood within the context of the algorithm by which transparency is generally computed and principles of additive color mixture, but can produce surprising results for the user.[5]

Using perceptual rules

Since most users do not want to become experts in human perception, our strategy is to incorporate guidance directly into the visualization software to aid in the the visual-design process.[5-8] In our approach, which we call Perceptual Rule-based Architecture for Visualizing Data Accurately (PRAVDA), rules filter the choices offered to the user, based on principles of human perception, attention, and color theory.

In the case of color-map selection, for example, we have constructed a library of color maps and a set of perceptual rules that constrain the set of color maps offered to the user. These rules are parameterized by metadata about data type, data spatial frequency, visualization task, and other design choices made by the user. Three color maps designed for different visualization tasks are compared with the default color map in Fig. 1. The isomorphic color map (upper right) is designed to produce a faithful representation of the structure in the data. In this color map, equal steps in data value correspond to equal perceptual steps in the color scale. The segmented color map (lower left) is designed to delineate regions visually. The highlighting color map (lower right) is designed to draw the user's attention to regions in the image that have certain characteristic features. This specific color map was designed to draw attention to areas that have data values near the median of the range.

The four color maps in Fig. 1 clearly demonstrate how different mappings of data onto color scales produce different representations of the data. The goal of our work is to understand how different information in the data is communicated by specific characteristics of the visual representation and to harness this knowledge so it can be used routinely in visualization. The rest of this article focuses on the color-map problem; we describe perceptual rules and metadata required to drive color-map selection.

Faithfully representing the structure

To represent accurately the structure in the data, we must try to understand the relationship between data structure and visual representation. For nominal data, objects should be distinguishably different, but since the data themselves are not ordered, there should be no perceptual ordering in the representation. For ordinal data, objects should be perceptually discriminable, but the ordering of the objects should be apparent in the representation. In interval data, equal steps in data value should appear as steps of equal perceived magnitude in the representation. In ratio data, values increase and decrease monotonically about a true zero or other threshold, which should be preserved in the data representation.

One important application of scientific visualization is to represent the magnitude of a variable at every spatial position. In many cases, the interpretation of the data depends on having the visual picture accurately represent the structure in the data. In order to represent interval data accurately, for example, the visual dimension chosen should appear continuous to the user. Candidate color maps that preserve the monotonic relationship between data values and perceived magnitude can be drawn from psychophysical scaling experiments. Stevens, for example, identified a set of sensory dimensions for which a monotonic increase in stimulus intensity produced a monotonic increase in perceived magnitude.[9] He found the shape of this relationship to be a power law, with each sensory dimension characterized by its exponent. Perceived magnitude obeys a power relationship with physical luminance over a large range of gray scales, which may explain why grayscale color maps are commonly used in medical imaging. Another dimension that displays this behavior is color saturation, the progression of a color from vivid to pastel.

The top row of Fig. 1 compares the effectiveness of the default color map and a color map designed to produce an isomorphic representation of interval data. Looking at the color bar for the default color map, we see bands of colors, not a gradual increase across the range. For example, nearly the entire range from 50 to 100 looks uniformly cyan. Although the data values change by almost a factor of two, all the values in this range look identical. This is also true for magnetic resonances in the range from 125 to 200, which appear to be green. This color map produces a contoured impression that masks the subtle variations in MRI intensity.

The isomorphic representation used in the upper right, although less dramatic, more accurately reflects the underlying structure in the data. In this color map, luminance and saturation both increase monotonically with data value. That is, brightness increases monotonically, and hue, which begins as a pure vivid blue, becomes more and more pastel. This color map produces a monotonic increase in perceived magnitude over the range. Using this color map, structures that are invisible using the rainbow-hue map can be easily seen. For example, the spatial structure in the midbrain and striate cortex that appears uniform green in the default map is highly detailed in the isomorphic map. Given the artifacts introduced by the default color map, we can easily understand why members of the medical community have been so cautious about adding color to their visual representations.

Importance of spatial frequency

Not all isomorphic color maps are appropriate for all data

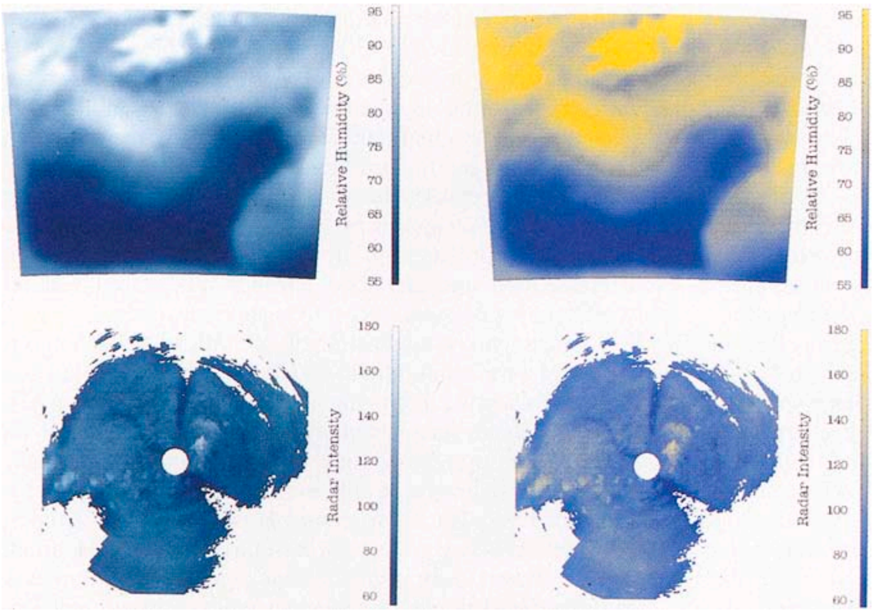

Figure 2. For effectiveness in visualization low- and high-spatial-frequency data should receive different treatments. Top row shows low-spatial-frequency data from a weather model. Bottom row shows high-spatial-frequency data from a radar scan. The high-frequency color map (left) reveals more detail in the radar data, whereas the low-frequency color map (right) reveals more structure in the weather data.

sets because different components of the color signal are processed differently by the human visual system. In particular, different components of the color signal have different spatial sensitivities. The luminance component in a color (the brightness/darkness component) is critical for carrying information about high-spatial-frequency variations in the data. If the color map does not contain a monotonic luminance (brightness/darkness) variation, fine-resolution information will not be seen. Conversely, the saturation and hue components in color are critical for carrying information about low-spatial-frequency variations in the data. A color map that varies only in luminance, such as a grayscale image, cannot adequately communicate information about gradual changes in the spatial structure of the data.

This means that the balance of luminance and saturation variation in an isomorphic color map depends on the spatial frequency of the data. Interval data with high spatial frequency call for a monotonic scale with a strong luminance component; interval data with low spatial frequency call for a monotonic scale with a strong saturation component.

These ideas are illustrated in Fig. 2, in which a luminance-based color map (left side) and saturation-based color map (right side) have been applied to low-spatial-frequency data (top) and high-spatial-frequency data (bottom). In all four cases, continuous data are mapped onto isomorphic color maps, and so contouring and other artifacts have already been eliminated. This figure thus highlights additional advantages of taking spatial frequency into account.

The data in the top row were generated by a weather model that computes, among other things, the variation in relative humidity over a geographic region. The structure of this low-spatial-frequency variation is practically lost when the data are depicted with a map designed for depicting high-spatial-frequency information (top left). The right-hand map, designed to expose low-spatial-frequency structure, gives the analyst more information, especially in regions where the humidity changes slowly over the geographic region, such as near the lower central portion below 65%. Also, in the lower right-hand corner of the image, the infusion of the high-humidity air into the low-humidity area is clearly seen as a yellow stream, virtually invisible with the color map intended for high-spatial-frequency data.

The images in the bottom row show a radial sweep from a weather radar sensor, measuring the high-spatial-frequency variation of reflected intensity (from thick clouds, for example). The high-spatial-frequency map (left) represents clearly the finely detailed structure of these data and also reveals sampling artifacts introduced by the sensor. The low-spatial-frequency color map (right) blurs the fine detail and, because the values above the mean are a different hue, puts inappropriate emphasis on these regions, shown in yellow.

Color maps for segmentation

The rules for providing isomorphic color maps for ratio and interval data are also effective in creating maps for segmenting data. The luminance component conveys monotonicity for high-spatial-frequency data, while the saturation component can be used to convey monotonicity in low-spa-

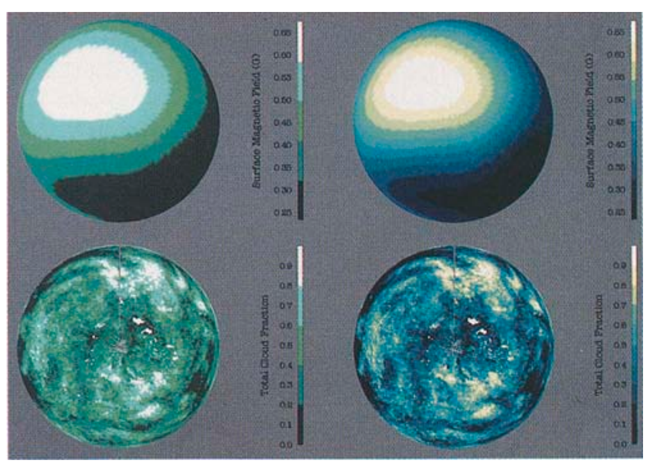

Figure 3. Fine-tuning the parameters of segmented color maps improves the visualization of low- and high-spatial-frequency data. Top row shows low-spatial-frequency data of Earth's magnetic field. Bottom row shows high-spatial-frequency cloud-fraction data. The high-frequency color map (right) reveals more information about the structure of the low-frequency data but reduces the information communicated for the high-frequency data.

Figure 4. Color highlights regions of interest in a visualization of remotely sensed data without disturbing the perceived spatial structure (right). Two left panels are two isomorphic color maps applied to the same image.

tial-frequency data. Since the steps are explicitly defined, however, luminance steps can also be effectively used for low-spatial-frequency data. In creating a segmented color map, it is important that the segments be discriminably different from one another. This discriminability limits the number of steps that can be represented. We have found that more steps can be effectively discriminated for low-spatial-frequency data than for high-spatial-frequency data.

Figure 3 shows a five-level segmented color map (left side) and a 10-level segmented color map (right side) applied to low-spatial-frequency data (top) and high-spatial-frequency data (bottom). For low-spatial-frequency data (top row), additional levels provide additional information. In this case, additional features of Earth's magnetic field in the Southern Hemisphere are revealed. For example, in the right-hand image, the gradient about the south magnetic pole is clearer. By contrast, additional features of the high-spatial-frequency cloud-fraction observations (bottom row) are not revealed by increasing the number of color-map steps, which effectively blur the segmentation.

Color maps for highlighting

Rules for selecting color maps that highlight particular features in the data can be drawn from the literature on attention.[10-11] Using these rules, we can construct color maps that highlight particular ranges in the data. An interesting extension of this approach is illustrated in Fig. 4, which displays data from the visible part of the spectrum remotely sensed from space. The left-hand panels display these data using two isomorphic color maps designed for high-spatial-frequency data. The right-hand panel shows how color can be used to highlight a region of interest without disturbing the perception of other aspects of the data. Across the entire image, the luminance component of the color map is identical. Within the regions of interest, however, the hue component has been varied, producing three distinct, semantically differentiable regions, one blue, one green, and one yellow. This method has been used successfully to mark regions of interest in the image and to highlight regions that display certain characteristics, such as those regions containing data that match a template.

Complementary visual techniques

An important task in visualization is to represent data from many sources simultaneously. The image at the top of Fig. 5 is derived from three spectral bands of a remotely sensed image. These data are displayed in a typical fashion, by mapping the values of each spectral band to levels of red, green, and blue. This representation provides a crude classification of the pixels.

Each pixel in the image has also been categorized into five classes with the help of an external land-use classification scheme. This land-use information could be displayed to the

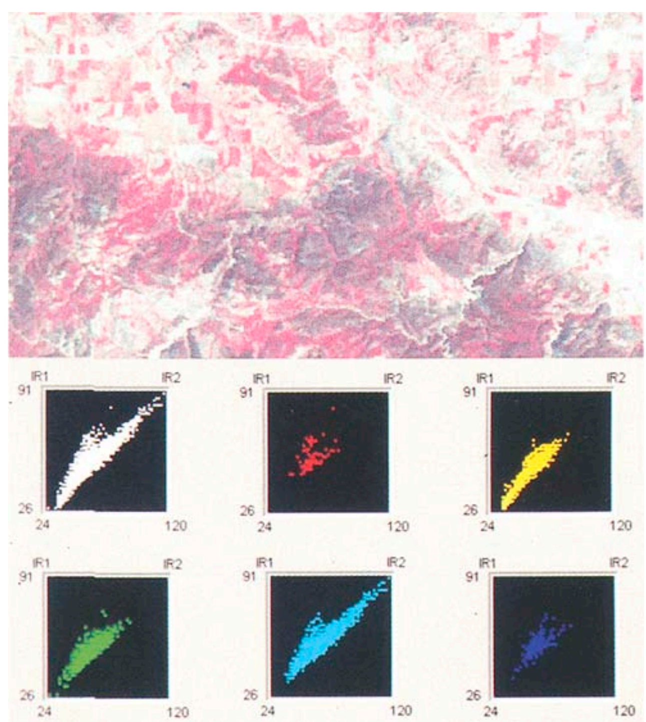

Figure 5. Application of a land-use classification model uncovers hidden relationships in remotely sensed data. Top figure shows a typical pixel-based color map. Bottom figure illustrates a graphical approach to examining differences between classes with respect to two spectral bands.

user by coloring the pixels according to class membership, with a different color for each class. If the spatial regions occupied by the classes are sufficiently large, each pixel could be mapped onto isoluminant blue, cyan, green, yellow, and red, as described above, to highlight the different categories without perturbing the spatial structure of the data.

The six panels on the bottom illustrate a complementary method for using color to understand the semantics of class membership. In this representation, each pixel has also been assigned a color according to its class membership. The coloring is used, however, to study the behavior of the different classes in terms of relationships among the various spectral bands. The top left plot shows the relationship between IR1 and IR2, the near-infrared and far-infrared bands. These bands are highly correlated (the correlation coefficient $r = 0.92$). The next five plots show this same relationship separately for each of the five classes. Visualization of this one bivariate relationship reveals that the "red" and "blue" classes are different from the whole population and from the other classes. There is a much smaller correlation between these two bands: The "green" and "yellow" classes are the only classes with low values in both infrared bands, and the "cyan" class is the only one with high values in both infrared bands. This type of analysis allows the user to gain insight into the semantics of class membership.

PRAVDAColor

Figure 6 shows the PRAVDA rule-based color map-selection tool incorporated into an IBM Visualization Data Explorer program.[12] In this visual program, imported data flow into a module called PRAVDAColor. PRAVDAColor computes metadata describing the spatial frequency of the data and the data type (such as ordinal, interval, or ratio) and asks the user to select the goal of the visual representation (such as isomorphic, segmentation, or highlighting) via a control-panel widget. These metadata flow to rules that constrain the set of color maps offered to the user. In the screen depicted in Fig. 6, three color maps are offered to the user. Since the simulated jet-engine-noise data shown in this example have low spatial frequency, are of interval type, and the task selected is isomorphic, these color maps all encode variations in magnitude as variations in the saturation of opponent-process pairs. Clicking on any of the color maps applies them directly to the data, and the user is free to vary the range of the color map. In this case, the full range of the first color map was selected, and the data are represented by a blue/yellow saturation scale.

Rule-based visualization

Modern systems for creating visualizations have evolved to the extent that nonexperts can create meaningful representations of their data. However, the process is still not easy enough, mainly because the visual effects of processing, realizing, and rendering data are not well understood by users, and the process of creating visualizations is largely ad hoc. Often countless iterations are undertaken to get a color right, to draw attention to a particular juxtaposition in the data, or to understand why a feature on the display screen does not seem to correlate to a physical phenomenon.

Our approach emphasizes a migration from a tool-based visualization system to a rule-based system that helps the user to navigate through a complex design space. Since the design process is iterative, the application of the rules is under interactive user control. The rules we have implemented so far draw on knowledge from the areas of human perception and color theory, but this structure could easily be extended to incorporate expertise from other domains. Our goal is to help users to make better, faster representations of their data.

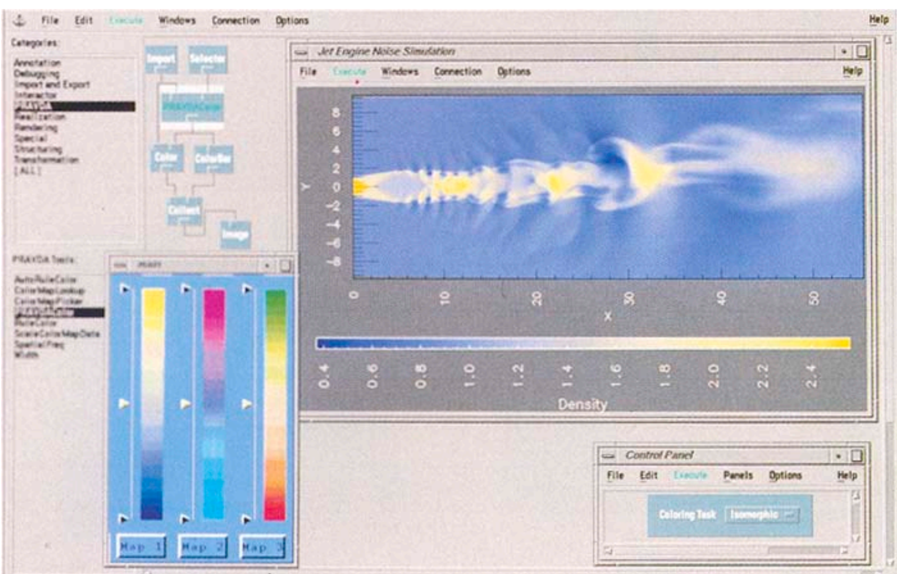

Figure 6. The PRAVDAColor offers users appropriate choices of color maps for representing data in a Data Explorer visual program. Here the rule-based system has offered choices appropriate for a low-spatial-frequency data set, the simulated jet-engine noise depicted in the window.

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available courtesy of CRAFT Inc., Dublin, PA. Remotely sensed images are available courtesy of Earth Resources Observation System Data Center, U.S. Geological Survey, Sioux Falls, SD.

The analysis and visualization at the bottom of Fig. 5 were produced using the Diamond software, which was developed at the IBM T. J. Watson Research Center and is marketed by SPSS Inc. (http://www.spss.com).

All other figures were produced with the IBM Visualization Data Explorer software, which was developed at the IBM T. J. Watson Research Center (http://www.almaden.ibm.com/dx).

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