Art, Affect and Color: Creating Engaging Expressive Scientific Visualization

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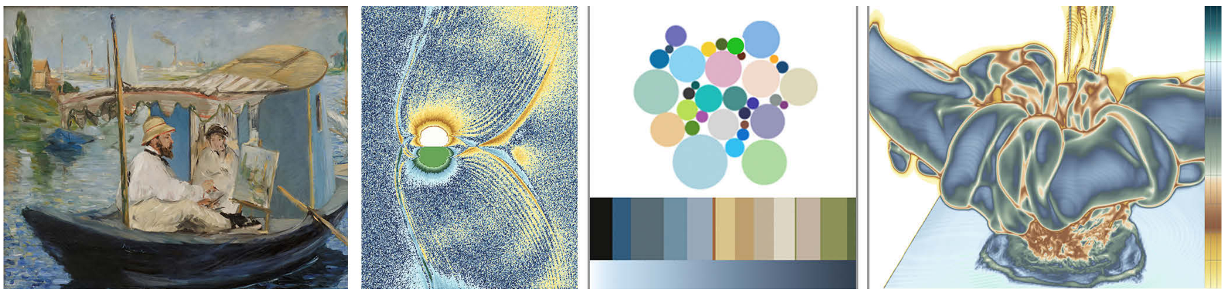

Figure 1: From left to Right: Edouard Manet's, *Monet in His Studio Boat*;magnetic reconnection simulation (Daughton, LANL)rendered in a color palette extracted from Manet's painting; Affect theory, the*calm* palette with the palette extracted from the Manet painting below;asteroid impact simulation (Gisler, LANL) rendered in the Manet palette.

Abstract

As the complexity of scientific data and the needs to communicate the science have grown, the requirements for visualization design and use have become more sophisticated. We increasingly need more effective ways of communicating the science across multiple audiences, including non-experts in the field. The challenges of enriching the representation have moved from the more naive ideas of making it "aesthetically attractive" to more profound constructs of visual language: how to enhance nuances in the data, and how to support more expressive visualizations that elicit different cognitive and communicative affect to tell the science story. In this paper, we describe how artistic color techniques drawn from paintings can be operationally applied to produce more evocative and informative scientific visualization. We illustrate how the color use in a painting can reveal structure and information priority and elicit affect using examples from current work with our scientific visualization colleagues. Our results highlight the value of engaging with artists in long-term, multidisciplinary science teams, but also emphasize the comprehension gaps that exist across the disciplines and the need for methods and techniques that bridge them so they are accessible to a wider range of data scientists. Our color extraction method is a small example of such a bridging technique.

Index Terms:

1 Introduction

The capability of the scientific community to present a clear, engaging, and accessible vehicle for understanding the principles upon which decisions will be made is critical to enhancing scientific insight and increasingly, to communicating the science to multiple audiences including non-experts in the field. These challenges relate to both information and affect: distilling the data into a visual representation that is simultaneously rich and comprehensible, and ensuring that the affective message - the experiential and emotional "tone" of the data story - is appropriately conveyed. These kinds of design, communication, and articulation skills are often foreign to scientists who simply want to "see the data" in the most detailed and expeditious way possible.

Our work bridges this gap by melding artistic and affective colour theory and applying them to the needs of scientists to build knowledge, techniques, and tools accessible to the individual scientist creating visualizations. In this paper, we present colour palettes extracted from paintings to demonstrate how principles from the artistic language of colour design combine with affective colour theory to create more evocative and informative scientific visualizations.

Our work provides scientists with (1) a theoretical overview of artistic and affective colour theory; (2) colour palettes that they can easily apply to their own work; (3) a guide for choosing the most appropriate palette based on their data structure and tasks; and (4) an explanation of how to apply a prefabricated palette to a data set using ColorMoves, a free online Scientific Visualization tool, (5) instructions for extracting an original palette from a piece of art.

2 Communicative Intent: Data to Language

Visualization researchers and scientists think of colour as a tool for exposing data whereas artists think of a visual language with its own semantic and expressive structures and scope. These are fundamentally different perspectives. The Oxford English Dictionary defines language as a "method of human communication, either spoken or written, consisting of the use of elements in a structured and conventional way; the phraseology and vocabulary of a particular profession, domain or group." We use language in three ways: *informative*: to communicate content; *expressive*: to convey feeling and evoke experiential response (affect); and *directive*: to command and/or prevent response and action [17]. These perspectives reflect the *communicative intents* of the creator, and understanding how how artists, visualization designers and scientists use visual language to define and construct those communicative intents is crucial to leveraging expertise from those disciplines to enhance the clarity and the affective impact of visualization. Scientists have languages all their own, typically based on mathematical constructs and honed for precise communication of results. Visualization designers look to communicate information in a structured easy to understand format. Artists, on the other hand, work to reflect myriad undercurrents (cultural, personal, experiential) and use a range of tools to con-

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nect and impact their audiences on an affective and reflective level. All use similar elements of visual vocabulary toward related and complementary goals but with different communicative intent and manipulations of emphasis, organization and technique.

To date visualization research and design has focused on the purely informative aspects of visual language, focusing on the perceptual and cognitive effectiveness of graphical representations of data to facilitate reasoning [23]. The objective of *effective* visualization design is to represent data with visual features for accurate cognitive interpretation. *Affective* visualization, on the other hand, uses visual features to evoke a mood, feeling or impression [27]. The affective context in which data representations are communicated and interpreted is often accidental or at best a secondary consideration, discussed as a topic of aesthetic design [18, 45]. While the importance of aesthetics and good design is acknowledged as fundamental to engagement, interest, and engagement, [18, 26, 44] this discourse has only touched in passing on the larger design space of affect. We argue that affect forms an important dimension of many visualizations. Its use in visualization applications is an emerging field of study in our traditionally *objective* discipline, as researchers identify its importance in data storytelling [7, 40], engagement and persuasion [28], cognitive enhancement [3, 10], and contextual framing [13].

Affective communication poses a particular challenge for the science community trained in precise accuracy but untrained in telling a story, emphasizing importance or eliciting engagement. This evocation of connection, feeling, reflection, or emotion is central to the creation of engaging experience: a communicative intent increasingly articulated by scientists who want non-experts to understand not only their data but also the import and implications of their findings.

Understanding colour, and how artists explore both the descriptive and the expressive richness of it, can increase both the clarity and the affective impact of a visualization. In this paper we present a means for the scientists to tap the affective potential of color while maintaining and enhancing the accuracy of their science.

3 Related Work

3.1 Colour in Scientific Visualization

There is a clear desire within the scientific community to use color to both increase the informative as well as affective properties of their visualizations, but guidance as well as an easy to implement system has been illusive. Numerous systems and tools for creating effective colormaps have been developed, many tied to artistic colour theory [5, 11, 21, 33, 47, 48] but adoption remains an issue. The scientific visualization community has largely relied on perceptual sciences to construct colour solutions [53]. However, increasingly, the scientific community understands the need to communicate more affectively by partnering with artists and designers [31,46,49,50,52]. Research centers such as NASA, NOAA, JPL and NSERC have collaborated with artists on scientific visualizations [8, 29].

Extracting palettes from art is not unexplored territory as documented in recent work by Phan, Lynch and others [19, 24, 30, 37, 38]. We build on this work by examining the intersections of affect colour theory and artistic color contrast theory and practice to build a methodology drawing from this combination.

While there is much debate about the characteristics of a *good* colormap. [4, 5, 22, 25, 34–36, 48, 53], that is not the focus of this paper. Zhou documented much of the colour work in the area in 2016. Several papers worth noting have followed [6, 12, 21, 30]. Our contribution rests on the combined application of artistic expertise and affect theory to engage and motivate audiences both within and beyond the scientific community. We present a means for scientists to create*affective* visualization [41,42,46,51], visualization designed to evoke a mood, feeling or impression. We address the need for awareness of colour impacts and how to use colour characteristics for engagement.

3.2 Affect Theory

Affect is a concept used in psychology to describe experiential response: feeling,impression, mood or emotion. It is typically classified by the well-known PAD model of affect [32] that plots them in a dimensional space defined by pleasure (valence) and arousal axes. Valence covers hedonic range, from positive (happiness, pleasure, love) to negative (pain, anger, sadness, fear). Arousal reflects intensity from calm (unaroused, relaxed, sleepy, etc.) to excited (high arousal, stimulated, nervous, alert, etc.). Typical emotions such as surprise, disgust or compassion can be placed in this 2D space (see Figure **??**); extensive emotion research has defined many more nuanced affects (such as affection or boredom) in this model as well. While designers and artists understand the more complex properties of palettes (organized groups of colours), there has been relatively little research specifically on the affect of palettes and visualization. Recently, Bartram et al.'s study of affective colour sets in visualization [27] showed that simple 5-colour combinations selected for categorical mappings differed significantly by affect. Figure **??** illustrates the most common colours selected for palettes for the four poles of the affect axes, where size represents frequency of use.

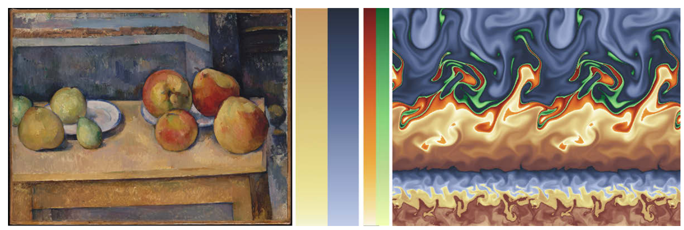

Figure 2: Secondary color palettes such as the one used here by Cezanne, evokes a sense of melancholy, a common affect of muted more nuanced hues. While the Manet in Figure 1 is also built using a muted palette, the reliance on primary hues enables it to maintain a positive affect.

These colours were selected from a set of 41 possible, and by definition their importance in the palette was normalized: that is, in categorical mapping, no palette colour had more inherent weight or importance than any other. Even in this limited colour space, there are clear patterns in the different affect groups. This study also looked at other palettes mapped to different affects located in the 2D affect space and found they combined colours from the 4 polar colour groups, reinforcing the correspondence between the validated PAD space and colour space. However, this work looked only at limited palettes and categorical mapping. We turn to artistic colour theory to enrich the affective understanding of more complex palettes and visualization applications.

3.3 Artistic Theory: The Language of Color

In 1960 Johannes Itten published The Art of Color: The Subjective Experience and Objective Rationale of Color examines symbolism of color, the emotional subjective feeling associated with hues and the contrasting objective colour principles [15]. The multifaceted approach to understanding color aligns directly with our approach to addressing the full capacity of color and its impact on scientific visualization. Color contrast theory was developed and refined over centuries but it was Itten, followed by Albers who formalized it's place as the foundation of painting practice and the basis upon which artists construct images.

Color contrast theory is the means used to systematically structure a painting, creating thematic relationships, visual categories and hierarchies within the work, allowing the viewer to visually determine the relative importance of various aspects of the work. We will discuss this in Section 5. First we need to define the terms and concepts underpinning artistic colour contrast theory.

3.3.1 Basic Definitions

Artistic colour contrast theory further characterizes colour contrast into seven types [16]. Below is a brief summary and other relevant color terminology.

1. Value Contrast: the range between white and black, light over dark.

2. Saturation Contrast: the purity of the colour; the amount of gray mixed in with the pure hue; fully saturated colors dominate lower saturation levels.

3. Complimentary Contrast: opposites on the colour wheel; red, green; blue; orange; and yellow purple.

4. Analogous contrast: hues adjacent to one another on the colour wheel, provides contrast with lower levels of colour interaction; yellow, green, blue and yellow, orange, red are the standards.

5. Cool/Warm Contrast: blues and greens are cool; reds to yellow are warm colours; warm over cool.

6. Contrast of Extension: the portion of area verses the visual weight of a colour. For example, to be in balance one would need only a small amount of red to balance a larger area of gray.

7. Simultaneity: vibration caused by two abutting saturated hues. This is a critical principal to consider in scientific visualization as the rainbow colormap is a perfect example.

8. Color Triad: three colours equally spaced the colour wheel: red, blue and yellow (primaries); orange, green and purple (secondaries).

Figure 10 diagrams these principals in Jan van Eyck's *The Arnolfini Wedding Portrait* painted in 1434.

3.4 Perceptual Science

Perceptual scientists consider color using the CIE model of three color axes or *channels*: blue-yellow, red-green and black-white (achromatic, related to lightness or more correctly luminance) [20, 48]. The properties of color common to visualization design from perceptual principles (see [43, 48] for a comprehensive discussion) are hue, saturation (or chroma, the colorfulness or distance from gray), and lightness, the value from black to white. Vision scientists define contrast as the difference in luminance or colour that makes an object (or its representation in an image or display) distinguishable from other objects and the background.

We note the different terminology used by artists and perception scientists while reinforcing the commonality of the larger constructs the terms identify. The concept of language use is more powerful, however: it is the structure of thought and a primary means of communication and shared understanding.

Perceptual colour theory is outside the scope of this paper, as we focus on affect and artistic colour theory, the impact of which has been studied less frequently in reference to scientific visualization.

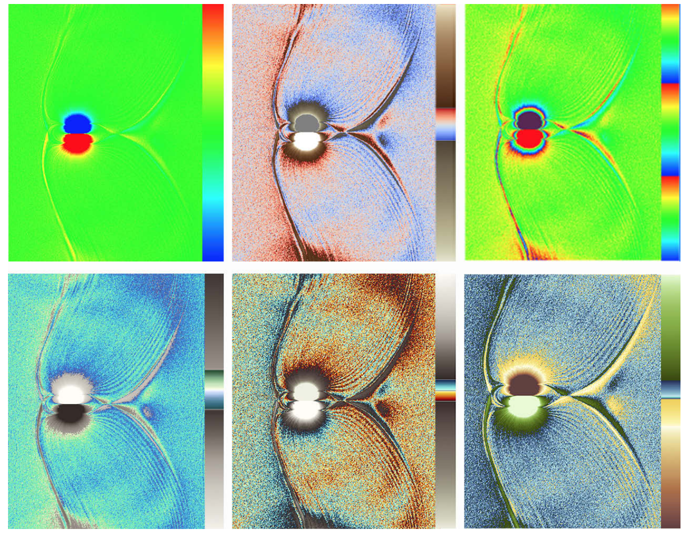

Figure 3: Here we show six versions of a magnetic reconnection simulation, Daughton, LANL. The top row shows examples in the cool warm and rainbow colormaps, the bottom row in comparative artistic palettes. See below for more detailed explanation.

4 Linking Affect, Artistic Color Theory and Scientific Tasks

This methodology blends knowledge discussed above from artistic and affective colour theory to enable scientists to create visualizations that are accurate, informative, and affectively engaging. The palettes and recommendations, all available on SciVisColor.org, enable scientists to easily explore their data, identify its features, and communicate its informative and expressive qualities.

Affective customized palette choices will assist scientists with engaging other scientists, funding agents, and the public. The environmental science community widely recognizes the need to frame issues like climate change using humanities-inflected modes of communication and interpretation like storytelling [14]. Hulme prioritizes the need for more engaging affective communication over further factual documentation as the goal is actionable change. Given the fundamental role of visualization in understanding climate science, incorporating methods from the arts and social sciences such as artistic colour theory and affect theory have the potential for impacting society.

As Figures 2, 6 and 5 demonstrate, artists use relationships between colour and the affects created by these relationships to construct the expressive meaning of a work of art. While designers and artists work with the interactive properties of colour and the perceptual community has contributed to the accuracy of color encoding data, there has been relatively little research specifically on the affect of visualization palettes. Recently, Bartram et al.'s study of affective colour sets in visualization [27] showed that simple 5-colour combinations selected for categorical mappings differed significantly by affect. Figure **??** illustrates the most common colours selected for palettes for the four poles of the affect axes, where size represents frequency of use. These studies are the foundation of the affect categories used in our methodology.

These colours were selected from a set of 41 possible hues. Even in this limited colour space, there are clear patterns in the different affect groups. This study also looked at other palettes mapped to different affects located in the 2D affect space and found combined colours from the four polar colour groups, reinforcing the correspondence between the validated PAD space and colour space.

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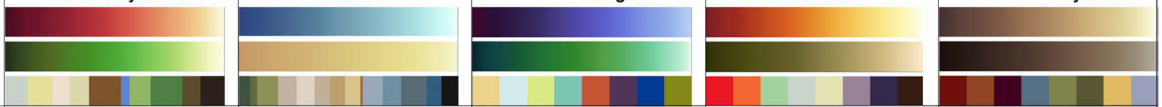

Artist	van Eyck	Manet	van Gogh	Picasso	Goya
data type	zero point data categorical data	continuous data noisy data	three categories	hierachies of importance	low detail data
task	communication feature id	exploration	communication	feature id communication	communication
affect	serious	calm	exciting		negative
color structure	categorical, context	equally important	two categories	hierachical importance	low levels of detail
color contrast	cool warm, saturation value, complimentary	analogous	secondary triad cool warm	cool warm, saturation hue	hue, saturation

Figure 4: Above is a chart detailing the alignments of artistic palettes, visualization tasks, data distributions and affect.

Figure 5: Goya's *The 3rd of May*, left, leaves no doubt that the subject matter is serious. The hues extracted from the painting, center align clearly with the hue set identified as serious in the affect study.

mapping, our extracted colour palettes extend the range, interaction impact, and affect to help scientists determine how they can use colour and *relationships between colours* to best tell the informative and affective story, taking into account their data structure and the tasks they need to perform.

As an introductory example to our methodology, consider Figure 1, which shows: Edouard Manet's 1874 painting *Monet in his Studio Boat*; a visualization of magnetic reconnection data in a palette extracted from the painting;

The affect of the visualization using the Manet palette mimics the affect of the painting. In the painting, we see how the use of an analogous, cool palette aligns affectively with emotions of calmness and pleasure. Though a mostly analogous palette, the use of muted ochre and orange, (warm tones that contrast with the blues of the painting and are associated affectively with excitation) on the triangular shape of the flags draws our focus to Monet and indicates that he is important to the piece's informational and affective terrain.

While we are considering the Manet palette notice Figure 3 comparing the magnetic reconnection data in six different colormaps. The top row shows: the data rendered in the standard rainbow; the cool warm narrowed to the center range of the data; the rainbow in a format used by scientists seeking more detail and the bottom row: a standard linear colormap moving through multiple analogous warm hues, in the narrowed data range; Samsel's blue orange divergent, in the reduced data range; and a customized distribution of the Manet palette, adjusted in ColorMoves. The rainbow reveals the issues with applying a standard clormap without adjustment. The cool warm, even in the narrowed range lacks both detail and affect. The triple rainbow does not lack impact, nor does it provide information or affect. On the lower row, a standard analogous cool hue range colormaps, in the narrowed data range provides the calm and positive affect. The blue orange divergent is shown in comparison to the cool warm map above, documents why wider hue ranges and or higher saturations are not always an advantage on noisy data. The final example employs the Manet colormap, in a customized structure aligning with the data, conducive to exploration and providing a means for feature identification.

Exploration is facilitated by the cool, analogous extracted palette aligns with the cluster of hues that affect theory identifies as calm. The calming affect combined with the analogous low contrast between the hues proves particularly useful when applied to noisy data sets like the magnetic reconnection data because its muted colors are distinguishable but not a strong contrast causing simultaneity vibration.

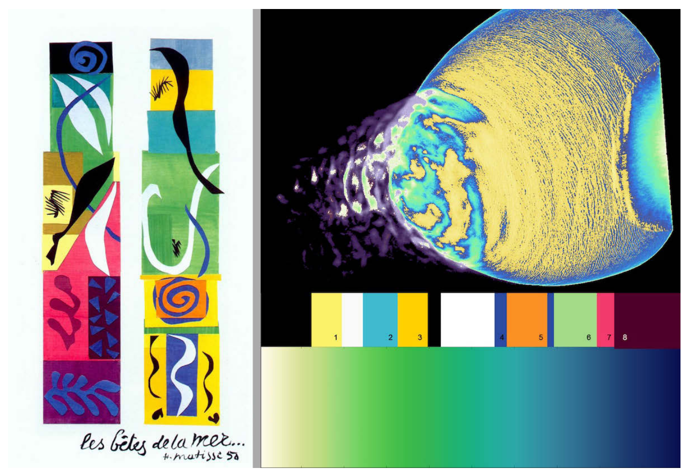

Figure 6: Matisse's *The Sea Beasts*, is comprised of crisp saturated hues directly aligned to the playful affect palette.

As Figure 5 demonstrates, Goya's use of value contrast aligns the painting with a hue set that affect theory identifies as serious, where browns have been associated with sad and stale ratings, contributing to its narrative that commemorates Spanish resistance to Napoleon's army during the Peninsular War. This palette provides significantly less internal contrast than the analogous Manet palette with the calm affect. Figure 6 demonstrates the opposite side of the spectrum, a wide fully saturated hue range and a playful affect.

5 Aligning the Palette

We have spoken a good deal about affect, colour contrast theory and artistic palettes. In this section, we demonstrate how these align to impact the informative quality given specific tasks common in visualization. With Figure 4, we provide a chart that maps out the relationship between artistic colour contrast theory, affect, data distribution, and visualization tasks, [34]. We present a few general

Figure 7: Here, *Seated Woman*, by Pablo Picasso is shown with a magnetic reconnection simulation in a cool warm colormap and a colormap constructed from a palette extracted from the painting. The simulation on the left is rendered in the standard cool warm colormaps and presents the data as equal in importance. The version to the right of the painting illustrates Picasso's palettes' ability to provide detail while directing attention in an orderly fashion to the areas of most importance. The far right image is the same magnetic reconnection simulation shown from a different view point. The structured colormapping enables align features across viewpoints.
Figure **??**

strategies for employing colour's inherent properties on different types of data and for different tasks. It is important to note that this is not a comprehensive guide, but instead a starting point for understanding alignments between colour theory, affect, and scientific data structure and needs.

One of the reasons that colour selection for scientific visualization is such a complex process stems from the interactive impacts of colour, studied in depth by Albers [1]. In scientific visualization, hues and their surrounding contrasts are determined by the distribution of the data rather than by the orchestration of the artist. Artistic knowledge and principals such as low saturation and analogous palettes can help alleviate unintended and often cacophonous interaction. The type and impact of colour interaction is primarily determined by the type and level of contrast which is why it is listed in a separate category.

5.1 Selection Variables

Our system takes employs the following categories with the noted variables.

1. Affect:positive; negative; exciting; calm; disturbing; serious; playful; and trust
2. Contrast types: hue; value; saturation;complimentary; cool warm; analogous; triads
3. Color palette distributions: unified; dual category; three categories; hierarchical; discrete
4. Scientist tasks: exploration, feature identification and communication
5. Data distributions: continuous, noisy; zero-point data; categorical and outliers of interest

Figure 4 contains a table with suggestions for selecting the best suited palette characteristics. While these are subjective, we have provided examples of each throughout the paper in order to demonstrate the results.

On one axis are the artists' palettes, and the other, the categories of tasks, data type, affects, colour contrast types, and colour structures. The grid is populated with recommendations aligning the specific palettes to the categories. Generally scientists know their task and overall data distribution, this is the starting point. Figure 4. outlines characteristics and usages in each artist's column. Select the one that most closely aligns with the data and scientific goals.

For example, if a scientist is working with a hierarchical data set, she might choose the colour palette extracted from Picasso's *Seated Woman*, a painting that employs varying degrees of saturation, a property closely associated with attention and thus able to direct a viewer's attention in sequence by applying the highest saturation to the area of importance and then descending in saturation and attention level simultaneously.

In Picasso's *Seated Woman*, your attention is first drawn to the red and black triangles, hues highest in saturation and value contrast, respectively. The yellows, bright green, and orange are the next to draw attention, followed distantly by the muted blue and yellow background, making it clear that the information in these areas is secondary.

6 Applying the Palette

After you have selected your palette, follow the steps below to apply the extracted palette to your data set using ColorMoves, sciviscolor.org/home/colormoves. Figure 8 provides a diagram of the process.
A. The first step, is to render your data in the *float colormap*.
B. Next, drag and drop the *float .png* into the ColorMoves interface.
C. The data will the appear in the default colormap.
D. Drag and drop the colour scales from the selection on the left into the histogram on the bottom.
E. Further refine the map by sliding the pins to identify the ideal span of each colour scale. The results can be compared to the widely used cool warm map.
One can also add discrete colours and export the colormap .png, .xml or .json for use in other visualization tools. Instructions on SciVisColor.org provide greater detail.

7 Extracting a Palette

As a practical matter, scientists generally do not have the time to explore historical approaches to painting to extract palettes and create specific affective custom colormaps. However, here we take a moment to diagram the underlying principles of how paintings are constructed, how one can extract palettes, and use them to build visu. See Figure 10.

1. Identify the dominant colors in the painting. By this we mean, which hues do you see first, second? Which cover the largest areas with in the painting? Next notice their characteristics. Do they span from light to dark? Saturated to unsaturated? Do they contain a wide or narrow hue range? The answers to these questions direct your colour scale choices.
2. Determine the information hierarchies. What are the most important variables in the data? You will be using the most dominant color scale for this variable. If your most important

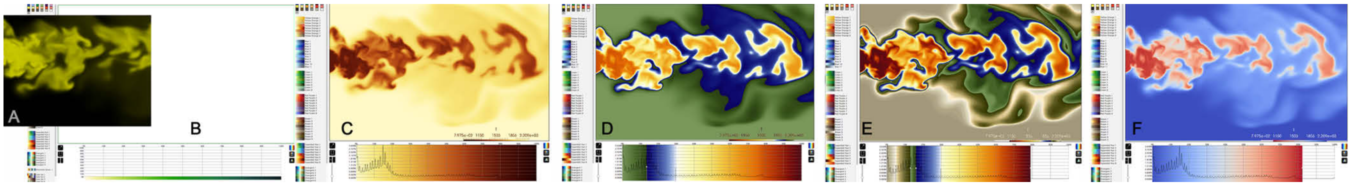

Figure 8: Steps for applying an artistic colour palette to data using ColorMoves.

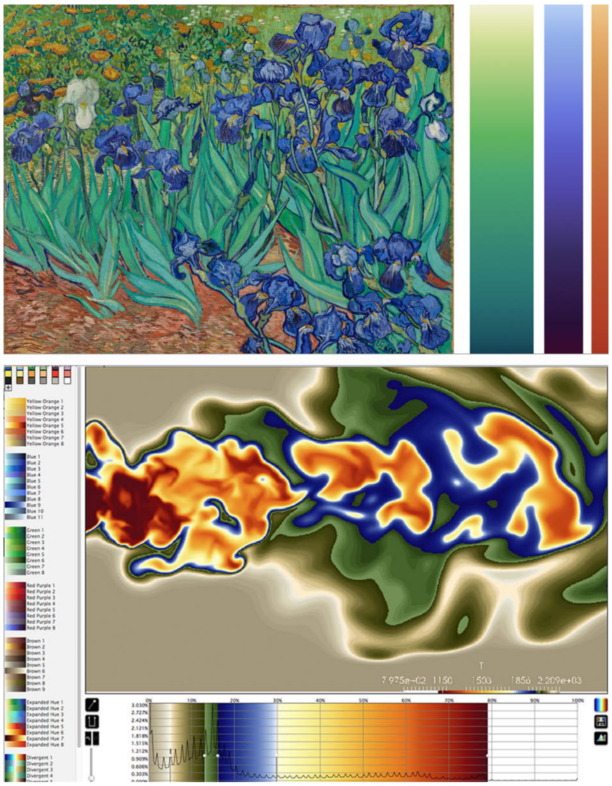

Figure 9: *Irises* by Vincent van Gogh employs a triad palette of secondary colors. While purple and orange surrounded by green is not a naturally associative set of hues for science domains, it is useful as a complimentary palette if one has multiple visualizations to compare. Combustion data shown here (J. Chen, Sandia) comes alive in Van Gogh's palette. Compare it with the cool warm example in Figure 8.

variable covers a large percentage of the visualization, you might follow van Eyck's lead and use the green scale, saving the potency of the red for equally important data that covers a smaller area. Neutral colour scales are applied to contextual areas.

For example, in the *The Arnolfini Wedding Portrait*, Figure 10, the primary colours are green, red, and brown. Red inheruntly projects the strongest attentive properties. Green is second being saturated and in the forefront of the image. Because ogf its foreground placement and larger area coverage, its contrast of extension is balanced with the more dominant red. Brown is a primary because it covers such a large percentage of the painting. That said, it is in a distance third place because it is a neutral, a totally unsaturated colour placed with two very saturated hues.

3. What other colours and color contrast types exist in the painting? In the van Eyck, the analogous relationship of the blue green and gold (E) as well as the lightness of the facial tones against the dark background(B and C) make up the secondary colour relationships. For a visualization these provide options for discrete colours representing related variables.

4. Context, sometimes considered background, impacts the hues and dominance of the primary features and require equal attention in their selection. What are the hues that provide context for the main themes within the painting? In the van Eyck, it is worth noting, that while the browns provide the context, quite a bit of detail can be rendered while maintaining the focus in the saturated areas (B, F and G). Used in communication, it enables clear focus and important context information. An example of the can be seen in Figure 11.

8 Discussion

8.1 Painting Selection

Colour usage varies widely by culture, tradition, available pigments, and location as well as time period. Most of paintings we examined come from the Western Artistic Tradition in the later part of the nineteenth century and early twentieth. We have focused on this movement and time period because of the intense exploration of colour and colour affect but also because these are the most contemporary works that fall outside of copyright range, sidestepping complications and expense.

Contemporary palettes have evolved and thus we have included one contemporary painting, the usage of which was generously granted by artist Brush Marsh, know for his ability to construct complex natural scenes from very narrow palettes. *River Stones*, an oil painting, demonstrates the ability of a narrow palette to convey complex information. Its narrow palette is in contrast to the other works included here, demonstrating the evolution in color in painting, and its growth through color field painting into current artistic practices [9]. Take a close look at the detail Marsh is able to extract from the narrow palette range. This is an interesting principal to bear in mind when selecting source material. The intensity of the surrounding hues have a major impact of our perception [1, 48].

The specific paintings were selected to align with a range of the affect theory palettes. Exploring palettes outside of the Western art tradition would provide a wider range of palettes, but is beyond the scope of this work.

8.2 Domain Convention

Domain convention plays an important role in color selection for scientific visualization. While we have considered individual domains in previous work [39], and the topic is certainly pertinent to this discussion, the range of domains and their conventions will span several papers in order to scratch the surface.

9 Limitations

Our approach brings several issues and potential drawbacks to the fore of the design discussion. While we have developed palettes by mining numerous paintings, our methods do not define nor identify appropriate paintings a priori, so the selection of a source artwork by a scientist may not guarantee the desired perceptual and affective impact. More critically, there are clear limitations and caveats to designing a Visualization for both effect and affect. Researchers and designers may be concerned that introducing or at least considering affective tone raises questions of data ”objectivity” and bias. We position our work here in the context of several critical points. First, data and representations are always curated, and bias and obfuscation are already present even if unintended: even without affective manipulation, we note that the color encoding maps currently in common use, especially the rainbow, are well know to distort and obscure data. Second, our goal is to aid scientists to tell their stories by providing a means to quickly and easily create engaging impactful visualizations. This requires a new level of responsibility on the creator’s part to make choices that are both *effectively* and *affectively* appropriate. If the communicative intent is to convey, engage and persuade, then affect becomes part of the design decision. But it does have to compromise the clarity of the science! We contend that *affect without effect is useless or misleading, but effect without affect is a missed opportunity*. We have developed and made available palettes for multivariate visualization that attempt to provide richeness in both affective and perceptual enhancement. The first draws on artistic artistic expertise while the second is grounded in color theory and design skills.

9.1 Validation

A key limitation of our work to date concerns validation. While the visualizations in this paper are actively used and are validated through iterative practice with scientists, we have not yet evaluated interpretative features through controlled studies. That said, the work stands on the centuries of expertise developed within the artistic community.

As we move into more nuanced expressions of affect and engagement, we intend to carry out more targeted studies testing the expressive scope of palettes. More generally, we have only touched the surface of the potential in mining the wealth of artistic knowledge and artifacts for visualization design methods. Beyond colour, representational forms include line, shape and texture; structure includes transparency [2], layering, and depth. What can we learn from other data representation abstractions beyond scalar colour? Future work may include: research of affective palettes for specific domains; recommendations for scientists in selecting palettes with the desired affect and appropriate structure; assessing the specific areas of value through iterative interviews with scientists included here and from other disciplines; and looking into contributions beyond the visual arts. While we have only begun to explore this intersection of art and data, our work seeks to extend the visualization discourse from the strictly informational to the more richly expressive.

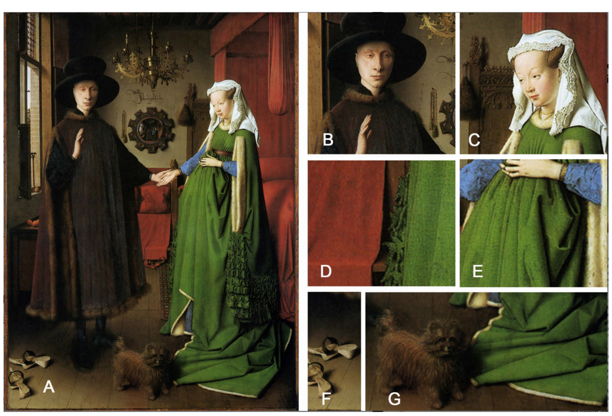

Figure 10: Jan van Eyck’s *The Arnolfini Wedding Portrait*, left and color contrast types, right: B. value contrast, C. saturation contrast, D. complimentary and cool warm contrast, E analogous contrast, muted hue value contrast,saturation contrast.

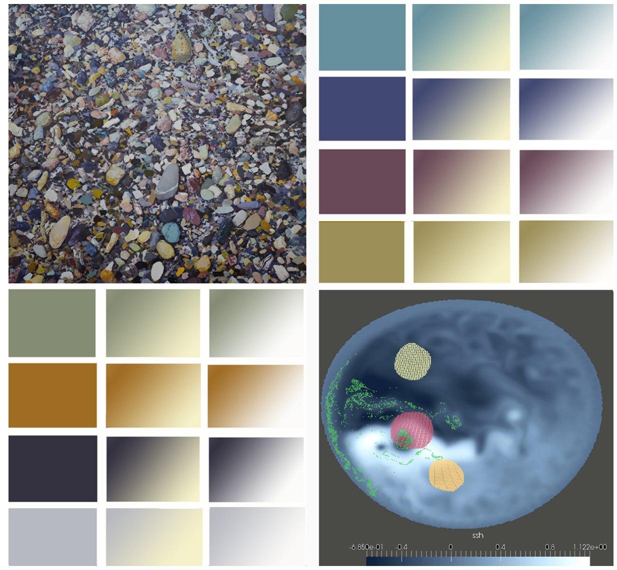

Figure 11: *River Stones*, an oil painting by Bruce Marsh on the top row accompanied by an extracted palette. Bottom: a warmer version of the extracted palette designed to contrast with the cool blue gray colormap forming the contextual background of visualization on the right, the MPAS Ocean model simulation, Wolfram, COSIM, LANL. The palette was designed to have equally weighted particle sets and contextual ocean current information. Marsh’s painting was an excellent fit for these goals because the palette is designed to provide equal weight through out the work.

10 Conclusion and Future Work

Our work highlights the impact of bridging existing affective color theory and artistic colour theory and in a format easily transfered to scientific data.

Affective palettes and color selections shown here are not all-inclusive or definitive. While they are representative of basic artistic and affect theories, they do not account for the full complexity that emerges from theorizations of relationships and interactions between colours. Future work includes expanding the colour set used in the affect study to include a wider range of hues and relationships drawn form artistic colour theory, such as the secondary color triads demonstrated in Figure 9, the painting’s secondary colors (green, orange and purple) form the base of the *Irises* palette, producing a powerful affective combination.

The purpose of our work is to provide scientists with an easy readily available means of creating engaging visualizations able to speak to our humanity as well as our intellect. To that end, all of the components needed to implement our system are available on line, free for all to use at SciVisColor.org.

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References

[1] J. Albers. *The Interaction of Color*. Yale University Press, New Haven CT, 2009.

[2] L. Bartram and A. Nakatani. What Makes Motion Meaningful? Affective Properties of Abstract Motion. *Image and Video Technology (PSIVT), 2010 Fourth Pacific-Rim Symposium on*, pp. 468–474, 2010.

[3] S. Bateman, R. L. Mandryk, C. Gutwin, A. Genest, D. McDine, and C. Brooks. Useful junk?: the effects of visual embellishment on comprehension and memorability of charts. *Proceedings of the ACM Conference on Human Factors in Computing Systems (CHI 2010)*, pp. 2573–2582, Apr. 2010.

[4] D. Borland and R. M. T. II. Rainbow color map (still) considered harmful. *IEEE Computer Graphics and Applications*, 27(2):14–17, 2007. doi: 10.1109/MCG.2007.46

[5] C. A. Brewer, G. W. Hatchard, and M. A. Harrower. Colorbrewer in print: A catalog of color schemes for maps. *Cartography and Geographic Information Science*, 30(1):5–32, 2003. doi: 10.1559/152304003100010929

[6] R. Bujack, T. L. Turton, F. Samsel, C. Ware, D. H. Rogers, and J. Ahrens. The good, the bad, and the ugly: A theoretical framework for the assessment of continuous colormaps. *IEEE Transactions on Visualization and Computer Graphics*, 2017.

[7] A. Cairo. Emotional Data Visualization: Periscopic's "U.S. Gun Deaths" and the Challenge of Uncertainty , apr 2013.

[8] D. Cox. Using the supercomputer to visualize higher dimensions: An artists contribution to scientific visualization. *Leonardo*, 41(4):391–400, 6 2008.

[9] P. Davies, W. Denny, F. Hofrichter, J.Jacobs, A.Roberts, and D. Simon. *Jansen's History of Art: The Western Tradition*. Pearson, New York NY, 8th ed., 2016. doi: 139780133884883

[10] L. Harrison, R. Chang, and A. Lu. Exploring the impact of emotion on visual judgement. In *Visual Analytics Science and Technology (VAST), 2012 IEEE Conference on*, pp. 227–228. IEEE, 2012.

[11] C. Healey. Choosing effective colours for data visualization. In *Proceedings of the 7th Conference on Visualization*, VIS 96, pp. 263–271, 1996.

[12] J. Heer and M. Stone. Color naming models for color selection, image editing and palette design. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, CHI '12, pp. 1007–1016. ACM, New York, NY, USA, 2012. doi: 10.1145/2207676.2208547

[13] J. Hullman and N. Diakopoulos. Visualization rhetoric: framing effects in narrative visualization. *IEEE Transactions on Visualization and Computer Graphics*, 17(12):2231–2240, Dec. 2011.

[14] M. Hulme. Meet the humanities. *Nature Climate Change*, 1(4):177–179, 07 2011. Copyright - Copyright Nature Publishing Group Jul 2011; Last updated - 2016-02-14.

[15] J. Itten. *The Art of Color: The Subjective Experience and Objective Rationale of Color*. Van Nostrand Reinhold, New York, NY, 1961.

[16] J. Itten and F. Birren. *The Elements of Color: A Treatise on the Color System of Johannes Itten Based on His Book the Art of Color*. Van Nostrand Reinhold Company, New York, NY, 1st ed., 1970.

[17] G. Kemerling. Language and logic, 2011.

[18] R. Kosara. Visualization Criticism - The Missing Link Between Information Visualization and Art. *Proceedings of the 11th International Conference on Information Visualization (IV 2007), IEEE*, pp. 631–636, July 2007.

[19] S. Lin and P. Hanrahan. Modeling how people extract color themes from images. In *ACM Human Factors in Computing Systems (CHI)*, 2013.

[20] K. Misue and H. Kitajima. Design tool of color schemes on the cielab space. In *2016 20th International Conference Information Visualisation (IV)*, pp. 33–38, July 2016. doi: 10.1109/IV.2016.24

[21] S. Mittelstädt, D. Jäckle, F. Stoffel, and D. Keim. Colorcat: Guided design of colormaps for combined analysis tasks. In *Proc. of the Eurographics Conference on Visualization (EuroVis 2015: Short Papers)*, vol. 2, 2015.

[22] K. Moreland. Diverging color maps for scientific visualization. In *Proceedings of the 5th International Symposium on Advances in Visual Computing, Part II*, ISVC '09, pp. 92–103, 2009.

[23] T. Munzner. *Visualization analysis and design*. CRC press, 2014.

[24] S. M. C. Nascimento, J. M. M. Linhares, C. A. R. João, K. Amano, C. Montagner, M. J. Melo, and M. Vilarigues. Estimating the colors of paintings. In A. Trémeau, R. Schettini, and S. Tominaga, eds., *Computational Color Imaging*, pp. 236–242. Springer International Publishing, Cham, 2015.

[25] M. Niccoli. The rainbow is dead... long live the rainbow! mycarta.wordpress.com/2012/05/29/the-rainbow-is-dead-long-live- the-rainbow-series-outline/, 2012.

[26] D. Norman. *Emotional Design: Why We Love (or Hate) Everyday Things*. User interface engineering. Basic Books, May 2005.

[27] M. S. P. Abisekh, L.Bartram. Affective color in visualization. In *Proceedings of the 2017 SIGCHI*, 2017.

[28] A. V. Pandey, A. Manivannan, O. Nov, M. Satterthwaite, and E. Bertini. The Persuasive Power of Data Visualization. *IEEE Transactions on Visualization and Computer Graphics*, 20(12):2211–2220.

[29] P.Fuller. *Five Artists at NOAA: A Casebook on Art in Public Places*. Real Comet Press, Seattle, WA, 1985.

[30] H. Q. Phan, H. Fu, and A. B. Chan. Color orchestra: Ordering color palettes for interpolation and prediction. *IEEE Transactions on Visualization and Computer Graphics*, 24(6):1942–1955, June 2018. doi: 10.1109/TVCG.2017.2697948

[31] A. Polli. Atmospherics/weather works: A spatialized meteorological data sonification project. *Leonardo*, 38(1):31–36, 2005.

[32] J. Posner, J. Russell, and B. s. Peterson. The circumplex model of affect: An integrative approach to affective neuroscience, cognitive development, and psychopathology. *Development and psychopathology*, 17(3):715–734, 2005.

[33] K. Reinecke, D. Flatla, and C. Brooks. Enabling designers to foresee which colors users cannot see. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*, CHI '16, pp. 2693–2704. ACM, New York, NY, USA, 2016. doi: 10.1145/2858036.2858077

[34] P. Rheingans and C. Landreth. Perceptual principles for effective visualizations. 02 2000.

[35] B. Rogowitz. Perceptual image similarity experiments. In *Electronic Imaging*, Photonics West'98, pp. 576–590, 1998.

[36] B. Rogowitz and A. Kalvin. The which blair project: A quick visual method for evaluating perceptual color maps. In *Proceedings Visualization 2001*, VIS'01, p. 183ff, 2001.

[37] E. C. S. Lee. Style classification and visualization of art paintings genre using self-organizing maps. 06 2016. doi: 10.1186/s13673-016-0063-4

[38] S. S. Lynch, J.Habber. Colourvis: Exploring colour in digital images. *Computers and Graphics*, 36(6):pp.1942–1955, 2012. doi: 10.1016/j.cag.2012.02.009

[39] F. Samsel, T. Turton, P. Wolfram, and R. Bujack. Intuitive Colormaps for Environmental Visualization. The Eurographics Association, 2017. doi: 10.2312/envirvis.20171105

[40] E. Segel and J. Heer. Narrative Visualization: Telling Stories with Data. *IEEE Transactions on Visualization and Computer Graphics*, 16(6):1139–1148, 2010.

[41] S. Silva, J. Madeira, and B. Santos. There is more to color scales than meets the eye: A review on the use of color in visualization. In *Information Visualization, 2007*, IV'07, pp. 943–950, 2007.

[42] S.Palmer, K.Schloss, and J. Sammartino. Visual aesthetics and human preference. *Annual Review of Psychology*, 64(1):77–107, 2013. doi: 101146120710100504

[43] M. Stone. *A field guide to digital color*. CRC Press, 2016.

[44] W. P. Su and B. Pham. Personality and emotion-based high-level control of affective story characters. *Visualization and Computer ...*, Dec. 2006.

[45] A. Vande Moere, M. Tomitsch, C. Wimmer, C. Boesch, and T. Grechenig. Evaluating the Effect of Style in Information Visualization. *IEEE Transactions on Visualization and Computer Graphics*, 18(12):2739–2748, Dec. 2012.

[46] F. Viegas and M. Wattenberg. *Artistic Data Visualization: Beyond Visual Analytics*, pp. 182–191. Springer Berlin Heidelberg, Berlin, Heidelberg, 2007. doi: 10.1007/978-3-540-73257-0_21

[47] C. Ware. Color sequences for univariate maps: theory, experiments and principles. *Computer Graphics and Applications, IEEE*, 8(5):41–49,

1988.
[48] C. Ware. *Information Visualization: Perception for Design*. Morgan Kaufman, San Francisco, CA, 3rd ed., 2012.
[49] R. West, J.Schulze, J.Gossmann, D. Tenedorio, and R. Singh. Algorithmic object as natural specimen: Meta shape grammar objects from atlas in silico. 2009.
[50] R. West, L. Monroe, M. Ford, and J. Aguilera. Art, science, and immersion: data-driven experiences. In *Proc. SPIE*, vol. 8649, 2013.
[51] M. Wijffelaars, R. Vliegen, J. V. Wijk, and E. V. D. Linden. Generating color palettes using intuitive parameters. *Computer Graphics Forum*, 27(3):743–750, 2008. doi: 10.1111/j.1467-8659.2008.01203.x
[52] S. Wilson. *Intersections of Art Science and Technology*. The MIT Press, Oxford, UK, 2002.
[53] L. Zhou and C. D. Hansen. A survey of colormaps in visualization. *IEEE Transactions on Visualization and Computer Graphics*, 22(8):2051–2069, Aug 2016.