Affective Color in Visualization

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ABSTRACT
Communicating the right affect, a feeling, experience or emotion, is critical in creating engaging visual communication. We carried out three studies examining how different color properties (lightness, chroma and hue) and different palette properties (combinations and distribution of colors) contribute to different affective interpretations in information visualization where the numbers of colors is typically smaller than the rich palettes used in design. Our results show how color and palette properties can be manipulated to achieve affective expressiveness even in the small sets of colors used for data encoding in information visualization.

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Affective Visualization; color Perception; Design

INTRODUCTION
We react emotionally as well as cognitively to visual imagery, and those emotions influence both how we use the information presented to us and how we are affected by its presence in our visual environment [34]. These systems are not independent; emotion can result from cognitive reasoning, and affect influences cognition [34]. Affect matters in visualization for communicative intent, engagement, and storytelling [6, 15]; there is evidence it supports problem solving [13]. While there is a long history of research and practice in how certain visual elements relate to affect, there is yet no framework of affective principles for visualization. The goal of our research is to examine the affective capacity of visual features such as color as part of this emerging framework.

Color palettes play a central role in data visualization where they are frequently used to map categorical attributes for effective discrimination and identification [39, 5]. Principles for using color to represent data in visualization are well established in the field and empirically validated [39, 5]. Designers and artists manipulate color to communicate affect but their knowledge of how to design affective palettes is largely rooted in professional craft and is qualitatively rather than empirically validated. Color psychology has proven the connection between individual colors and affect, but to date there are no studies in how combinations of colors (palettes) may convey different affect in the limited scope used in categorical information visualization.

Unlike the rich palettes available to design applications, mapping colors to categorical data (the most common use of color in visualization) introduces two important constraints. First, the usable scale of the palette is small: typically, 5-10 colors [42]. Second, the colors need to be strongly perceptually distinct [39]. We are interested in validated computational models of how color relates to desired affect in these constrained palettes.

We had two basic research questions. First, can we relate certain affective impressions to properties of a color palette in abstract images such as simple visualizations? And second, what might this mean operationally for the design of affective color palettes that are useful in information visualization? We note an important point here. This work asks: given a desired affect, what palette colors should you choose? It does not answer the broader and much harder question: given an arbitrary palette, what affect does it convey? Our goal is not to absolutely link color and affect for all cases. Instead, we propose that simply being able to recommend statistically likely palettes for a particular affect is useful to visualization practitioners.

In this paper, we report three studies examining how different properties of color palettes were associated with specific affective impressions. Our results show relations between perceptual color properties (hue, chroma and lightness), palette composition (hue clusters, color frequency) and certain types of affect. This research makes the following contributions. First, our results affirm the potential of color for conveying meaning and identify initial palettes that enhance these affective impressions even in the limited space of information visualization palettes. Second, our findings support initial guidelines based on the distribution of hue, chroma and lightness for the affects we studied. Some are very distinct, while others overlap. Third, we propose a new method for modeling palettes using social network analysis that shows some interesting relationships between colors in palettes worth further exploration. These results extend research in design practice and introduce new dimensions of expressivity to visualization.

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AFFECTIVE VISUALIZATION

The role of affect in information visualization applications is emerging, as researchers identify its importance in narrative [6, 36], problem solving [13, 33, 16] and contextual framing. The fundamental difference between data and affective visualization is in communicative intent. Information visualization seeks to **represent** data with visual features for effective cognitive interpretation. Affective visualization uses visual features to **evoke** a mood, feeling or impression. These are commonly described by factor-based classifications such as the well-known PAD model of affect [35] 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; extensive emotion research has defined many more nuanced affects (such as affection or boredom) in this model as well [23].

RELATED WORK

Color psychology examines the interplay between color, cognition, affect and behaviour, considering factors of culture [8, 31], emotional response [40, 21] and behavioural influence (particularly around consumer response) [24, 22, 3]. Various studies show that "warm" colors (red, yellow and orange) are more arousing than "cool" hues of blue and green [32, 3]. Red is considered hot, vibrant and intense across cultures [22, 31, 9], and most likely to induce arousal and anxiety [21]. It is also tightly coupled with semantic cultural meaning, and thus varies in its association with valence. Yellow, orange and brown have less consistency of affective response, although yellow is also considered exciting. A study of website color for e-commerce across cultures found that respondents disliked the yellow scheme, terming it "too showy" and not "appropriately professional" [8]. Studies also associate brown with "sad" and "stale" ratings [31]. Blue, and to a lesser extent green, have positive links to the natural world and are associated with positive content [31, 32, 9, 10]. In particular, blue is strongly associated with peacefulness and calm across cultures [8, 31]. In advertising, blue is associated with trust [8] and competence [22]: it evokes stronger buying impulses than red [3]. Alternately, in room color, blue is more likely to be associated with depression, and red with anxiety [21]. Clearly context is a critical moderating factor in these findings.

Most color psychology has focused on hue rather than chroma and lightness, although recent studies show the influence of lightness and chroma on affective response [24]. High chroma color is exciting and intense; low chroma colors are calmer and less dominant. Greys have been described as "serious" and "professional". Lightness is associated with calm: lighter colors are considered more pleasant, less arousing and less dominant than dark colors [22, 24]. Black is negative and dominant [31, 40]; dark browns are sad. In one study, subjects were less upset when they read about murder on light pink paper than on white [40]. These findings may be useful when hue choice is limited by branding or other assignment, because lightness and chroma can be altered without contravening categorical meaning or desired "personality." [32]

COLOR, AFFECT AND AESTHETICS

Aesthetic principles for palette design are typically based on color harmony, an attempt to model which colors work together visually. This is commonly expressed as geometries with respect to hue wheel, as well as careful control of lightness variation [17, 41]. Itten's qualitatively grounded contrast model formalized the concepts of warm and cool colors, and postulated that tints (light colors) represent the brighter and better aspects of life, while shades (dark colors) represent the darker, sad, and negative forces [17]. Itten contrasts have been used in image analysis of affective colors [30] and aesthetic color selections [29].

Relatively little research has examined color palettes and affect. Madden identified two strategies of color association in logo design (which colors are used together): consistency (colors have a similar meaning) and complementarity (each color is associated with a different meaning) [31]. He found that when blue was used as the designated logo color, it was most often paired with white, green and yellow (largely a consistency strategy). In contrast, when red was the designated main color, respondents preferred a complementary strategy, with the secondary color different across cultures.

PALETTE GENERATION

Foundational work in color naming [4] showed that all cultures have common concepts of a small set of basic colors and their associated verbal names. Heer and Stone built a probabilistic model of color naming [14], showing how it can map between colors and names and measure color similarity. They applied this to compare and evaluate palette design, where minimizing name overlap and maximizing saliency are important for comprehension and memorability [39]. This work was expanded to semantic color design for visualization by Lin et al. [25] and Setlur and Stone [37] for finding appropriate colors associated with categories. These algorithms explore the rich associations grounded in the concept-color relations of objects and identities, but have not been applied to more nuanced terms of emotion, atmosphere or affect.

Color-word associations have long been explored as the basis for palette design using different strategies: manual selection from a predesigned set of colors linked to a particular word or concept, such as the Kobayashi color Image [20] or the Adobe Kuler website; or automatic color extraction and combinations given a set of rules using concepts of color harmony [28, 7]; perceptual contrast [19], keyword-color scales [38] and user pair preferences [11]. Kobayashi's empirically grounded color Image Scale [20] provides 130 basic colors combined in 1170 three-color combinations indexed by 180 keywords such as "provocative" or "romantic," a complex set of expressive concepts. Lindner et. al. used color-word associations and harmonic color themes based on the color wheel for automatic palette generation in which the user described the semantic content and the color extraction algorithm determines the appropriate colors from a precomputed color thesaurus [27] that matches a word to its underlying distribution in HSV[28]. In a small user study they compared their palettes to Adobe Kuler's user-generated palettes and found no significant improvement, concluding that color palette preferences are highly influenced by personal taste. Jahanian et al. [18] took a different approach, using a color extraction method for magazine design palettes based on word association with the concepts in the Kobayashi scale [18]. More recently, researchers have explored automated palette generation for the sparser palettes in visualization. Wijffelaars et al. developed a generalized method based on sampling of a continuous path through color space at uniform intervals [43] with no user input into the generation. In contrast, Colorgorical is an interactive tool for automatic palette generation that uses a sampling based on user discriminability and preferences in which users can customize the sampled selections. [11].

COLOR METRICS

Perceptually-based color metrics can be computationally represented as geometries in a three dimensional color space. The common CIELAB representation offers a color distance metric ΔE. This is simply the Euclidean distance between two colors, expressed by their coordinates, L^*, a^*, b^*. Using polar coordinates to represent a^*, b^* creates a more intuitive representation. The radial distance, C^* defines chroma or relative saturation, hue is defined by the hue angle, $h°$. In this paper, we simplify this notation to L,C,H. We also use the terms 'lightness,' 'chroma' and 'hue' for these quantities. We also use the term 'saturated' and 'desaturated' descriptively to describe high and low chroma colors respectively.

Quantitative measures to represent color palettes are more complex. Lin et al. analyzed them using color distance metrics to extract distinct palettes from images [26]. These included mean, min and max distances between colors in themes. Two quantitative approaches to measuring hue variation are entropy (how distinct the colors are) or saturation-weighted hue dispersion [WHD], which calculates the angular dispersion between hues along the hue wheel, taking saturation into account[12]. When WHD is higher, hues are more concentrated (less dispersed). Methods such as k-means clustering are commonly used to model color associations [25].

MOTIVATION: AFFECT AND COLOR

We were curious whether color and affect would be linked in simple 5-color categorical palettes applied to common visualizations. Are there different groupings of colors that align more consistently to areas in that space? Can the relative differences suggest palette selection based on the desired affect's "location" in the PAD affect space? In other words, if an affect combines **Calm** and **Positive**, would the colors selected for it be similar to colors in palettes selected in both? Our work differs from other concept-color association research in two ways. First, we focus on palettes rather than only single colors. Second, we explore whether color associations along the valence and arousal dimensions map to PAD space such that color selection for other affects reflects their relative influence.

We began by selecting 8 affects. The 4 "core affects" of **Calm, Exciting** and **Positive, Negative** represented the valence and arousal dimensions of the PAD model. We added 4 "pragmatic" affects: **Serious, Playful, Trustworthy** and **Disturbing**. We chose these as examples in a much larger space rather than as definitive "best" options in quantifying exact mappings. These can be considered as combinations of the core affects. **Disturbing** is **Exciting+Negative**; **Playful** is **Exciting+Positive**; **Trustworthy** is **Calm+Positive**; **Serious** is **Calm+ Negative** (although the valence may be less pronounced). We realize that these might not produce exactly equally weighted locations in the affect space, where other emotions such as "Happy" might. But we have a second important design goal: ecological validity. Emotions such as happy or sad may not be of interest in visualization applications, but trust and serious are important affects in business communication [8]. Playful, serious and disturbing are relevant to storytelling, an emerging field in data visualization [6, 15].

APPROACH

We explored color-affect relations in three studies. First (S1), we analyzed the color palettes of tagged images in two large social network databases, Flickr and deviantArt.com. From these results, we generated a set of colors for a design study (S2) in which users selected 5 colors for categorical coloring in simple visualizations to best communicate a specified affect. The results of S2 produced both distinct patterns for color selection and grouping by affect and a new metric of palette weight. We then ran a validation study (S3) in which we generated palettes based on this metric and asked users to rank them for the specified affect. We discuss each in turn.

STUDY 1: IMAGE ANALYSIS

Following [25], we analyzed the palettes of 8608 images. We selected these by searching for images tagged with terms related to our eight affects, and then eliminating all images with humans or human-influenced scenes (such as war images) to avoid conflation with content [23]. Roughly 2/3 of these images were abstract; the remaining 1/3 were landscapes, still-life/object, or nature scenes.

For each image, we calculated mean lightness and chroma. We then computed distribution histograms with a bin size of 10, calculating the percentage of pixels in the image that was in the lightness or chroma range of the bin. We generated 8 sets of 40 distinct hues each using k-means clustering, plus lightness and chromaticity ranges obtained from the image analysis. For

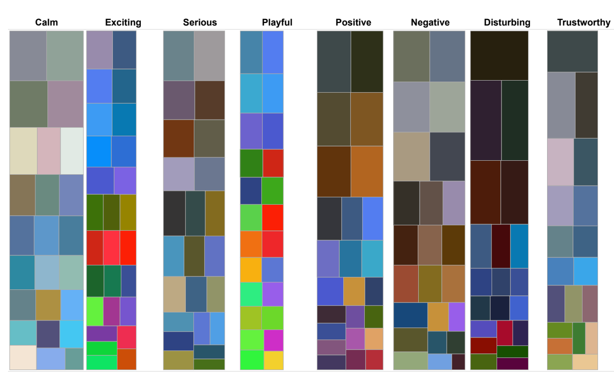

Figure 1. Most common colors by affect in image analysis study (S1)

each hue, we calculated the probability of a candidate color c from the set given an affect value and corresponding image histogram using Lin's algorithm [25]. Each hue was measured against the set of different images that were categorized by affect. We then selected the most commonly used colors in each of the affective image sets (Figure 1).

Results

As our data distribution was marginally non-normal, we used the Kruskal-Wallis test for significance (the rank-based non-parametric equivalent of an ANOVA for multi-factor data). Affect had a significant effect on both lightness X^2 (7, 8607) =199.6250, p<.0001 and chroma X^2 (7, 8607) =387.7106, p<.0001. **Calm, Playful** and **Exciting** images were lighter than **Disturbing** and **Negative**. **Negative** and **Calm** were less saturated than **Playful** and **Exciting**. We see patterns in **Calm** palettes containing a larger concentration of light and desaturated blues and greens. **Trustworthy** also has blues, purples and some greens. **Playful** and **Exciting** use highly saturated colors like reds, vibrant greens and blues with **Exciting** having relatively more dark reds. **Disturbing** has a larger distribution of dark browns, blues, reds and black. **Negative** used more grey and muted browns. With the exception of **Positive**, these results mirror what color psychology would predict. We were surprised by the amount of browns and dark colors in **Positive**.

STUDY 2: USER-DESIGNED PALETTES

We used these results to design colors for a user study. We asked a visualization color expert to design a smaller set for use in our next study. She reduced the set to 36 colors, using a combination of k-means clustering to combine similar colors, and filtering to remove colors that were either too light to offer sufficient contrast with the background or too dark for the hues to be easily visible when small. She then used visual tools and visualizations of the associated color metrics to establish that the resulting colors offered a balanced mix of CIELAB hue, chroma and lightness values.

We ran a pilot study where people with design experience created palettes based on affect. The goal of our study was to see whether they would consistently assign different color sets for each of our 8 affective categories in simple visualization tasks. The results from the pilot showed affect strongly influenced colors chosen, similar to those in Study 1. We then expanded our study to a wider population, to see if the results were specific to designers and to get a larger data sample. We extended the color set to 41 colors, adding more dark, because our results indicated that the original palette did not provide quite enough different colors for some of the darker affects. We show the detailed results for this larger experiment.

Method

Participants completed categorical coloring tasks for two simple visualizations (bar chart or map) using the interface shown in Figure 2 to select palettes of 5 colors for each task from a set of 41. We chose a map and a bar chart as they are familiar information representations. Participants were instructed to select colors to convey an affect from our eight affective categories. They were not told what the data represented other than affective intent. They could additionally modify the palette

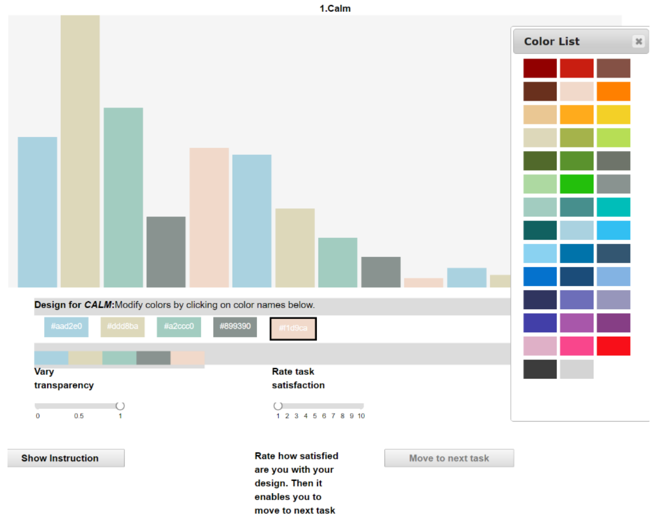

Figure 2. Study 2 interface

overall balance by adjusting a slider to control alpha. When the participant was finished with the color selection, s/he rated satisfaction using a slider between 0 and 10 to indicate how successfully s/he felt the colors expressed the concept. At the beginning of each trial the initial alpha value was set to 1 and the visualizations were colored in neutral gray.

Because we were interested in the relative locations of color groups in the PAD space, we paired endpoint tasks of the affect model **(Calm-Exciting, Positive-Negative)** to establish differences (if any), drawing from the core theoretical work in mapping affect. Similarly, we considered these differences in the pragmatic case **(Serious-Playful)** with clear semantic opposites. Where there was not a clear opposite **(Trustworthy, Disturbing)** we did not pair the tasks but presented them singly. This provided a relative rather than an absolute measure of how palettes might differ with respect to comparative affect. We used this design because we are not expecting to be able to absolutely quantify all possible palettes with respect to affect, but rather to understand what might make a desired affective impression comparatively stronger or weaker. In the cases of Trustworthy and Disturbing (both affects with strong ecological validity that are not clear opposites), we simply sought to see how they might relate to the other affect groupings.

Each affect task was independent and required separate color assignments, alpha and satisfaction rating. Participants could reassign the 5 colors in the palettes until satisfied: they were not constrained to mapping a color to a particular spatial location or size in the visualization. The experiment began with a training task in which participants colored Happy and Sad affects. No time limit was set on training; participants proceeded to the main study when ready. The experiment was hosted on our university web server. People could stop at any time, and login to the system later to complete the study: the system retained state. We report only on results where all tasks were completed.

Factors and metrics

We had two independent variables: Affect (8) and Visualization (2: bar chart, US map). Our raw dependent variables were color metrics (lightness, chroma, hue), alpha, and satisfaction rating.

Hypotheses for Study 2

H1. Affect will influence color choice. Cooler colors will be used for low arousal **(Calm, Serious and Trustworthy)**. High arousal affects **(Exciting, Disturbing, Playful)** will use warmer colors: more reds, browns and oranges. **Positive** affects **(Positive, Playful, Trustworthy)** will include more green. **Negative** will use brown and grey.

H2. Affect will have a significant effect on lightness: **Calm** colors will be lighter, **Negative** ones darker.

H3. Affect will have a significant effect on chroma: high arousal affects **(Exciting, Playful, Disturbing)** will include more saturated colors.

Design

We used a 2-way between-subjects design separated by Visualization type, producing an experiment session of 8 experimental conditions (1 Affect) per group. Trial ordering was randomized and block ordering was counterbalanced. A 76x8 design yielded 608 trials.

Participants

76 persons, roughly distributed by gender, with normal or corrected-to-normal vision, were paid to participate. They were randomly assigned to one of the 2 groups (Bar or Map).

Results

We removed all palettes that were either incomplete or included duplicate colors, giving us 504 palettes that each had 5 unique colors. We then did both visual and statistical analysis. Figure 3 shows the resulting palette colors. Each bubble represents a color that appeared in a palette in the associated affect; the size represents how frequently it was used. Zero frequency values are removed, and each bubble cluster has a slightly different number of bubbles (colors) in it. However, the size scale is the same across all the affects.

We clearly see that colors and color characteristics varied by affect, confirming H1. We used a a nonparametric Kruskal-Wallis for significance for all tests. Visualization type had no effect, so we combine the results in subsequent discussion. A statistical analysis on the three perceptual metrics, lightness, chroma and hue, found all were significant. We found significant effects for affect on lightness X^2 (7, 1216) =426.7211, p<.0001 and chroma X^2 (7, 1216) =481.8955, p<.0001. **Calm, Playful** and **Positive** were much lighter than **Disturbing, Serious and Negative**. **Calm** was the least saturated of the affects; **Exciting, Playful** and **Positive** the most colorful (chromatic). While alpha was significant, the effect was very small: it was only applied in **Calm**. Since this effect was small and simply reinforced the already strong pattern of high lightness and low chroma for this affect, we did not use alpha in further analysis. These results statistically confirm our

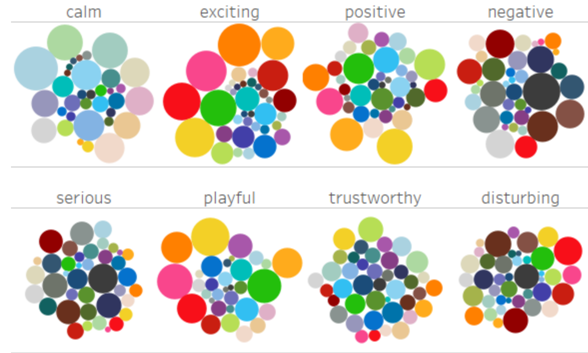

Figure 3. Frequency distribution of colors by affect (S2).

hypotheses H2 that lightness relates to valence **(Calm, Positive, Negative, Playful) Trust** and H3 that arousal influences colorfulness choices **(Exciting, Playful vs Calm, Serious)**. We also saw a combined effect: both valence and arousal influence color choice, notably in **Calm** which is both lightest and least chromatic. Satisfaction rating was uniformly high and never significant.

Affect was highly significant for hue: X^2 (7, 1216) =93.4. We calculated color dispersion in each palette as saturation-weighted hue dispersion (WHD) and saw significant differences by affect: X^2 (7, 1216) =88.21, p<.0001. Colors in **Exciting, Playful** and **Positive** were most spread out in hue space; **Calm** and **Negative** palettes were the most tightly clustered.

Looking at the core affects, we note some clear patterns. **Calm**, as predicted, makes strong use of cool colors (blues and greens) and is overall high lightness and low chroma. **Exciting** emphasizes warmer and higher chroma colors: more reds and yellows. **Positive**, like **Exciting**, uses strongly saturated hues but incorporates more green. **Negative**, as anticipated, has more browns, dark reds, and greys. These patterns combine in interesting ways when we consider the pragmatic affects. **Playful** is both **Exciting** and **Positive** in affect: its colors are similar to **Exciting**, but included more greens and yellows and fewer reds than **Exciting**. **Serious** shared the greys of **Negative** but used more blue; we would expect that it has aspects of low arousal and **Calm**. Notably, **Serious**, which might be considered both calmer than **Disturbing** and less **Negative**, used fewer red and yellow hues. **Disturbing**, which is clearly **Exciting** and **Negative**, reflects the browns and greys of **Negative** but incorporates more of the reds and yellows of **Exciting**. **Calm** and **Negative** palettes were the most tightly clustered. These findings and the statistical analysis confirm H1.

STUDY 3: USER RANKED PALETTES

We now wanted to validate these results and to assess an algorithmic design metric. We used insights from S2 to design sets of palettes for each affect and ran a study in which people selected the best and worst palette for an affect from a set of 5 choices. To avoid any bias potentially introduced by the pairings in Study 2, affects were presented singly. For each affect, we calculated the weight of each color as how often that color was used in a palette in S2. We then calculated palette weight for each palette in S2 as a sum of its color weights.

Figure 4. Examples of good (high weight) and bad (low weight) palettes

Given that high palette weight represented the cumulative strongest color combinations for that affect, we conjectured it would be a good predictor of a palette's suitability for a particular affect. We designed palettes for S3 manually based on weight. For each affect, we automatically generated every possible combination of 5 colors (749, 398 sets) and calculated the palette weight of each. We then sorted the list from highest to lowest and manually selected candidate palettes from three relative areas: the top weighted palettes, the lowest weighted palettes and the middle area. We used manual selection to minimize color replication in the palettes, as this was difficult in the highest weighted palettes because there were a few very heavily weighted colors in these: we ensured that no two palettes shared more than 3 colors. Figure 4 shows examples of two good (top weight) and 2 bad (low weight) palettes for each of **Calm** and **Negative**.

Method

In each trial a participant saw 5 spatially identical bar charts, each colored with a different palette (Figure 5). Colors in the palette were randomly assigned to locations in the bar chart. The participant was asked to identify one as Best and one as Worst. There were 8 affective tasks. For each affective category there were 15 possible palettes, binned into 5 "good", 5 "medium" and 5 "bad". These were only used for randomization: in each trial, 2 palettes were randomly selected from the "good" bin, 1 from the "medium" bin and 2 from the "bad" bin. Each participant did 2 repetitions of each affective task (2 Best, 2 Worst). Affect tasks were presented in random order.

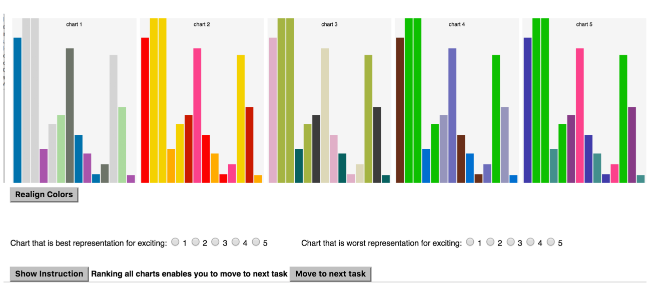

Figure 5. Study 3 Interface: Users ranked the Best and Worst of 5 palettes for each affect in S3.

Metrics

The independent variables were affect and palette weight (PW). The dependent variable was the rating of Best/Worst for each palette. For each palette we thus had the rating, the individual colors in that palette, the frequency weight for each color and the summed palette weight.

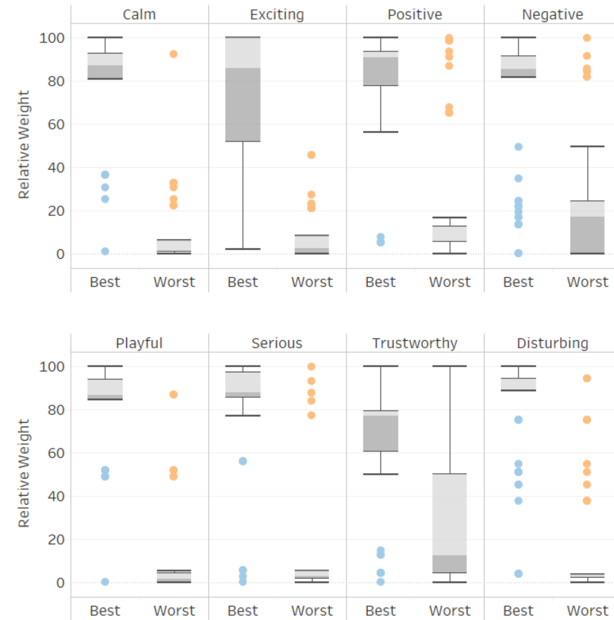

Figure 6. Palette Ranking by relative weight and affect (Study 3)

Hypotheses Study 3

H4. Higher weighted palettes would be more likely to be rated Best than low weighted palettes;

H5. Lower weighted palettes would be more likely to be rated as Worst.

Participants

38 users (and an additional 2 with incomplete data) participated. They were roughly distributed by gender. All had normal or corrected-to-normal vision. Participants were entered into a draw for potential reimbursement. None had taken part in the previous studies.

Results

Figure 6 shows the results of palette ratings by weight and affect. As the palette sets were very different in the **range of weights**, we normalized the weight metric to **relative weight position**: that is, the percentage of the overall range that the weight represented. So, for example, the Calm range was 135 from the lowest weight to the highest weight: a Calm palette with a weight of 109 had a relative weighted position of 80.7. We then used a logistic regression analysis to determine if this would be a significant predictor of Best/Worst choice. The result was extremely significant:X^2 (1, 1218) =1093.32, $p<.0001$.

These results confirm that palettes are more likely to be ranked better as their weight increases. Conversely, palettes with low weight were more likely to be selected as Worst. These results confirm **H4** and **H5** that palette weight calculated from our previous studies proved a strong predictor of how people ranked it for affect expressivity. More generally, they validate our essential conjectures that even simple palettes of 5 colors can convey different affective impressions, though it can been seen in Figures 3 and 7 that is a stronger finding for some affects than others. In particular, we note that the relative

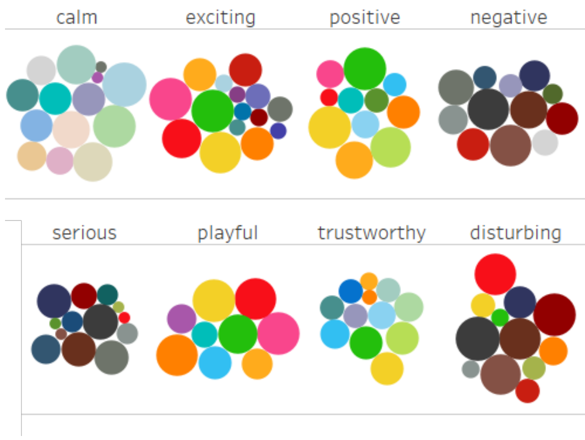

Figure 7. Colors from palettes chosen as "Best" in Study 3

difference between Best and Worst in the more nuanced affect of **Trustworthy** was smaller, and there were more outliers. We surmise this was due to the case that the range of weights in these palettes were smaller: instead of a few highly weighted colors, the preferred colors were more evenly used, and thus the weight ranges were smaller. This raises questions about what else we might need to understand about what contributes to color selection for affective palettes. We calculated the preferred colors for each affect by counting how many times the hues occur in the palettes rated Best for that affect. We then simply selected the colors with the highest count for each affect. Figure 7 shows the preferred colors for each of the affects in Study 3. These strongly reflect the results from S2. If pairing had introduced bias in S2, we would not have seen these confirmatory results in S3, as there were no comparative paired presentations in this study.

PALETTES AS SOCIAL NETWORKS

These results show that there are patterns of color preference by affect. To explore the relationship between colors in palettes, we tried modeling palettes as social networks. Social network analysis provides both a visual and a mathematical analysis of actors (nodes) and relationships (links) to give insight into the various roles and groupings in a network: where are the most influential nodes? What are the strongest connections? Are there clusters? In particular, measures of network centrality identify the most important nodes in the network as a function of how well they are connected to other nodes; models of network structure identify clusters and outliers. While we have no formal results, our analysis was interesting enough that we provide a few examples here.

Using the Gephi library [2],we modeled each palette as a connected subset of 5 colors, where each color Ci was a node in the network of colors and an edge Eij indicated Ci and Cj were used in the same palette. Each of the 8 affect groups was a separate network of our 41 palette colors. This enabled us to see not only the frequency of individual color use but also structural patterns (combinations of colors).

We visualized these palettes as networks using a force-directed layout algorithm. Color frequency is mapped to node size; pairwise frequency (weight) to edge thickness. For clarity, we removed all color combinations with an edge weight less than 3, showing only pairwise combinations used in 3 or more palettes. Figures 8 and 9 show the resulting networks. Node size (frequency of color use) reflects the results of Study 2 and 3. The network structures emphasize which colors are highly connected, which are outliers. Some palettes cluster tightly around a small number of key colors (**Calm, Exciting, Playful**). Some are more angular and spread out. And then

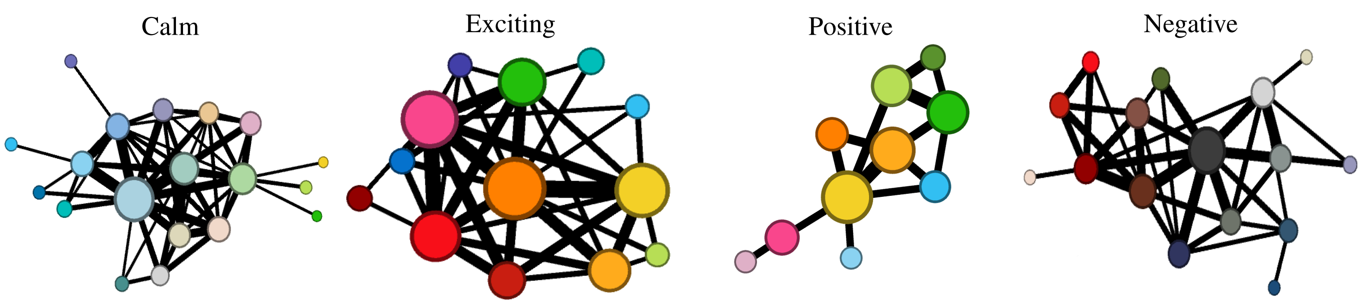

Figure 8. Core Affect Combinations

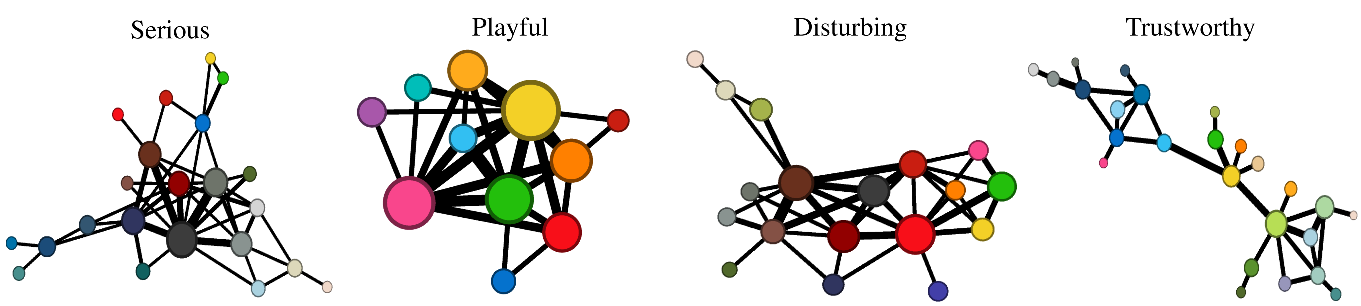

Figure 9. Pragmatic Affect Combinations

there is **Trustworthy**. In the frequency models,**Trustworthy** showed very little structure. It included many colors, fairly uniformly weighted. Here, we see a distinct structure, with two groups linked by yellow. We hope to find further insight by continuing this sort of modeling in the future.

DISCUSSION

What do these results tell us? First and foremost, we are able to reliably associate color and palette properties with affective response even in the limited scope of color selection in simple information visualization representations, extending previous work in individual color-affect relations. Our studies show that both the perceptual properties of small color sets, and the composition patterns of how they are used together, are affectively distinct. From our studies in image analysis (S1) and user-designed palettes (S2), we were able to algorithmically define a simple metric of palette weight based on color frequency use for each affect that proved a reliable predictor of preferred affective palettes in a final validation study (S3).

We see consistent patterns in lightness related to affect across all studies. **Calm, Playful, Positive** and to a lesser extent **Trustworthy** are lightest, while **Serious, Disturbing** and **Negative** are darker. This confirms H1. Similarly, we also saw consistent use of higher chroma colors for **Playful, Exciting, Positive** and **Disturbing**: where **Calm, Serious** and to a lesser extent **Trustworthy** were less saturated. These comparisons are significant, and confirm our hypotheses that lightness and chroma are linked to affect. This indicates that any color set intended for use in expressing these affects must provide enough variation in both lightness and chroma.

One of our primary goals in this is to create guidelines for design and design evaluation simple enough to be programmed, similar to work by Bartram et al. [1]. While these will never replace the skill of an experienced designer, they can reduce the time spent exploring options that simply don't work and provide reasonable starting grounds for further refinement.

Figure 10 summarizes the mapping between affect and color metrics for each affect. Here, each of lightness, chroma and hue have been mapped to a common range, then plotted. For hue, the important metric is whether the colors are warm or cool. We make this easier to see by rotating the hue angle by 60 degrees so that low values are cool, high values are warm. The resulting metrics are labeled (NL, NC, N SH). The box plots show the distributions. Our hypothesis of hue association with affect is supported by these distributions.

Based on the results of study 3, we speculate that if a palette contains colors near the median of L,C,H for a specific affect, then the resulting palette is likely to be judged as matching that affect, especially if the distribution is tight. Some affects have clearer L,C,H "profiles" than others. Of the Core affects, **Calm** is the strongest, requiring high L, low C and cool colors. **Negative** has similar properties for C and H, but dark colors predominate. **Exciting** and **Positive**, however, while distinctly different than **Calm** and **Negative**, are not very different from each other, or from the pragmatic affect **Playful**. The profiles in the other pragmatic affects show similar overlaps, as we might expect. This is why we need more nuanced analysis

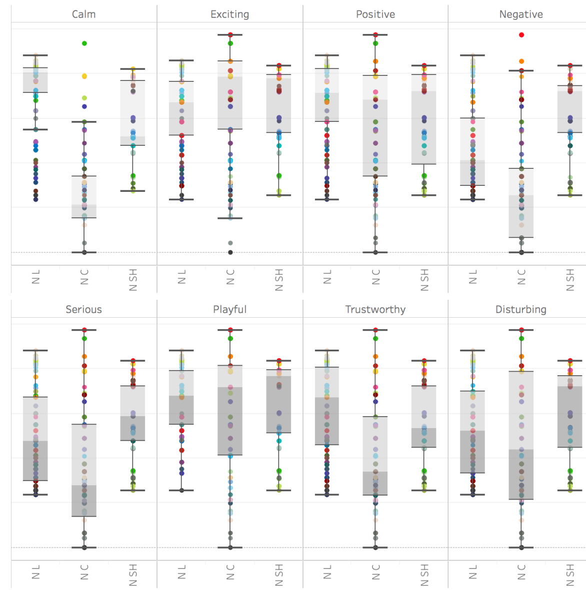

Figure 8. The L,C,H distributions for each affect. Hue is rotated by 60°to group warm and cool colors, all values are normalized to a common range

about which colors go with others, as we are exploring in the network diagrams.

While we cannot reliably profile each affect, even being able to say what colors to avoid for specific affects can be useful. For example, we can say with some authority that highly saturated light colors will NOT be appropriate for **Serious** or **Trust**, or **Calm**; light blues, beiges and greys are never likely to convey **Playful**; dark red and browns are not **Positive**; and light colors, particularly green, do not communicate **Negative** affect.

The network models help us visualize palette composition patterns: groupings that show what colors are likely to be used together. Certain affects showed different palette composition patterns, **Calm, Exciting and Playful** palettes tightly clustered around the main colors, confirming high co-occurrence of these colors in most palettes. In contrast, certain colors in Positive were only used in combination with bright yellow. Greens form an important cluster in **Positive**. **Serious, Negative** and **Disturbing** palettes show loose sub clusters anchored by a central set of core colors. **Trustworthy** shows a clear example of two thematic strategies (blue-gray, green-gray) bridged by a single common color (yellow). In future work, we hope to better understand what these patterns mean and how they might be applied.

We sought to see if there were general color associations with the more abstract dimensions of valence **(Positive-Negative)** and arousal **(Calm-Exciting)** that would translate (lend color elements) to the specific expressions of **Playful, Serious, Trustworthy and Disturbing**. We certainly saw evidence of these crossovers in our limited set of results. Establishing such reliable associations leads to the question of if and how we might algorithmically determine color selection based on the desired affect's location in the PAD affect space. In other words, given a desire to enhance a visualization as more "reassuring", for example, can we quantify where "reassuring" plots between **Calm-Exciting** and **Positive-Negative** and determine the relative hues, chroma and lightness values as a weighted contribution from each? In future work, we plan to explore how the color patterns we see in the core affects may generalize to other pragmatic affects.

LIMITATIONS

While these results indicate the potential for using color to communicate affect, we note several limitations to our studies. We have studied exactly one palette size (5 colors) for a limited set of visualization forms (bar charts and maps), on a white background. While we have confirmed that color and affect can be linked even for these simple, functional cases and speculate that the results have broader value than precisely what we tested, we obviously don't know how far our results can be extended.

Which colors compose an effective palette depends on the size of the features they color. In our studies, all of the features colored were large enough that all of the study colors were easy to perceive and distinguish. The study color set reflected these image constraints. To support fine-grained graphs such as line charts and scatter plots, some of the colors in our study palette would be too light, or would be too difficult to differentiate. We would need a different set of study colors. We hypothesize that we we would see similar palette trends for such graphs, even though the detailed color statistics would be different.

There are many other factors that can influence the affect induced by an image, including cultural color identities, spatial properties such as relative size and juxtapositions, and ultimately, the subject matter. Our work deliberately tries to minimize these influences, as including them would be much more complicated.

We tested only a limited range of affective impressions in abstract contexts. This speaks to the need for more basic research in examining a fuller range of affect, and more applied research in examining the expressive capacity of affective palettes in actual visualization use.

Finally, even within our constraints, our results do not offer unique guidance for each affect as was discussed above. Clearly our current color statistics are not enough. However, the network models do offer some further directions to pursue.

CONCLUSIONS

The first goal of this work was to demonstrate whether color can express affect, even when used as categorical coloring for simple data visualizations. While some may find our results unsurprising, there are many others who expressed skepticism. This study demonstrates clearly that affect is a dimension of categorical color palette design, and motivates extending work in automated palette design to include affective concepts. This brings new dimensions of expressivity and communicative scope to visualization.

Our results show a validated relationship between affect, perceptual color properties (hue, chroma and lightness), and palette composition for the eight categories we measured. This confirms and extends findings in color psychology and design practice to the context of simple information visualization forms and data contexts. While this is not enough to clearly distinguish all affects, it helps limit the design space, which can be of significant practical value. For example, one could extend Colorgorical[11] to include affect by using L, C and H filters.

A more challenging application would be to include affect in the design of palettes where some colors are already defined, especially if they fall outside of the simple L,C,H model of affect. A simple example would be creating a Trustworthy palette for T-Mobile that included its signature bright purple. Here, we would ideally be able to model how to combine that playful colors with others to create an overall Trustworthy affect.

In addition, we introduce network modeling as a method to characterize palette composition. We are concerned not with individual color selection per se, but in the much more difficult to quantify sets of colors and how they are combined (the palette). Our network models begin to provide some insight on how single colors that might be individually strong in one affect may still be combined in a palette more suited to another affect (such as the yellow in Trustworthy). While preliminary, we believe this approach holds promise for exploring richer design options with color combinations based on more sophisticated social network metrics.

Our work suggests ways to address this that would be interesting to explore further. For example, the psychological dimensions of affect (arousal and valence) are shown to be strongly influenced by lightness and chroma. This indicates that these properties can be used to "tune" palettes of predefined hues to these affects, either by modulating the color itself, or by optimizing these values over the palette as a whole. The work in network modeling suggests, for example, that with a more complete model there may be ways to combine the T-Mobile playful purple with other colors to still convey an overall Trustworthy affect.

Finally, we stress that we have approached this research from a perspective of design rather than pure perceptual theory. Our work asks: given a desired affect, what palette colors should you choose? It does not answer the broader and much harder question: given an arbitrary palette, what affect does it convey? To make this distinction concrete, if the goal is a **Calm** affect, our results suggest light, cool, pastel colors. If your goal is to create a **Disturbing** affect, then dark colors, especially reds, are better. Our results cannot reliably tell you whether a palette of pastels plus a vibrant blood red (which might well be Disturbing depending on how the red is used) is Calm or Disturbing. Being able to absolutely relate color to affect for all cases was not our goal: frankly, we don't believe this is possible. However, we do believe that simply being able to recommend validated palettes for a particular affect will prove of interest to those who create and employ visualizations. Clearly, there is much work to be done.

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