Reflections on the Uses and Available Choices of Categorical Colorschemes

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Abstract: Categorical colorschemes must respect a number of criteria — mainly, they need to incorporate a number of easily distinguishable colors, and they need to avoid giving to the reader the impression that the colors in the visualization have particular relationships. Crafting these palettes requires careful attention to the distribution of colors; thus, for a long time, visualization designers have been relying on a limited choice of readily available palettes. Although such palettes have been proven practical and functional, our own experience with designing visualizations had us struggle repeatedly with the limited choice, the feeling of repetitiveness in seeing the same colors in visualization papers, and a number of other limitations that we discuss in the paper. In this document, we discuss some properties of the most common categorical colorschemes, and propose a method to generate new palettes that are comparable in properties to the existing ones.

1 INTRODUCTION

Colorschemes can be classified in a few categories: the main ones are *continuous* (either diverging, cyclical, sequential) and *categorical*. The choice on which type to use is entirely based on the type of data that one has to deal with, and the tasks and objectives of the resulting visualization, but in this paper we are going to take a particularly close look at the *categorical* type of colorscheme.

A categorical colorscheme is used in data visualization to represent discrete categories of data. Unlike continuous colorschemes, which display a gradient of colors to represent a range of values, categorical colorschemes use distinctly different colors to differentiate between discrete groups or categories. This makes them particularly useful for visualizing nominal or categorical data, where each category is unrelated to the others and does not imply a specific order.

Categorical colorschemes must have the following characteristics:

- Each color in a categorical scheme is chosen to **stand out from the others** to make each category distinguishable at a glance.
- The colors **do not imply any numerical or ordinal relationship** between the categories they represent. For example, using red, blue, and green to represent different species of animals implies no inherent order or classification among them.
- They aim for **balance in color perception**, avoiding bright or dull colors unless visualization has a specific requirement to emphasize certain categories.

One of the most popular options for finding categorical palettes is colorbrewer (Harrower and Brewer, 2003). At the time of writing, the 2003 paper that accompanies the widely used website has 1508 citations, and the count excludes all the papers and visualization designs that use it without citing it. Colorbrewer is often widely recommended because the palettes it offers are claimed to be perceptually balanced and robust to various conditions such as colorblindness, viewing in grayscale, and printing. Colorbrewer palettes are included in other software packages, such as Chroma.js (Aisch, nd), or visualization packages such as Seaborn (Waskom, 2021).

Another popular choice among visualization designers is to explore the selection of color palettes included as part of d3 (Bostock et al., 2011) (table 1) — indeed, as d3 is the library of choice for many visualization designers, picking directly from the library's offerings is speedy and comfortable. D3 of-

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fers 10 palettes — however, it should be noted that 8 of these palettes are taken directly from colorbrewer. The remaining two are tableau10 and category10, both palettes coming from tableau software and designed by their own designers, as explained in their blog post (Stone, 2016) detailing how the palettes were created. Very recently, a new one, observable10, was included to replace tableau10 as a default in observable (Pettiross, 2014).

Harrower and Brewer, in their paper on colorbrewer (Harrower and Brewer, 2003), describe the design process of the colorschemes they offer as such:

> *The sets of color schemes in ColorBrewer were designed using both experience and trial and error.*

From this paper, we draw the conclusion that the palettes were the product of a design process based on experience and intuition, and not an algorithmically precise distribution of the colors uniformly in a colorspace. This might be considered a possible source of errors, accompanied with the fact that, in the same paper, the colorschemes were not tested with a user study. Additionally, the authors designed the tool with geographical maps in mind — as proven by the fact that the paper is published in a geography journal and that the only sample visualization presented is a map. This can lead to overlooking the specific properties and needs of other types of visualizations. Moreover, the shorter palettes introduced in the tool are just a sliced version of the longer ones.

Countless visualization papers have validated most of the potential issues by using these palettes and testing their readability and overall practicality. Nevertheless, one persistent problem remains: the limited range of choices. The same palettes are repeatedly used in visualization research, causing a repetitiveness in vis papers that abuse the same colorschemes. Any creative attempts to develop new colorschemes must be (rightfully) justified. The choice is even more limited when we consider that not even all the palettes proposed are designed for uniform colorschemes (see, for instance, Accent in Table 1). This limitation can hinder the creative process, and we ourselves have struggled over and over in finding appropriate categorical palettes.

We want to argue for openness to a more creative process in the ability to select colorschemes, and more freedom in picking colors. Indeed, if the initial design of the colorbrewer palettes was obtained through trial and error, then it is in the realm of possibilities that we do the same with newly formulated palettes. The same free, intuitive design process was used for the Tableau colorschemes. The research around programmatically formulating colorschemes is ample — as we discuss in Section 2. However, in our experience, none of these produces satisfying results out of the box, and there always seem to be something missing — a creative eye, disconnected from entirely logical formulations. Perhaps, the need for human input is proven by the fact that all the palettes offered as defaults in d3 are the results of an intuitive design sense rather than exclusively programmatically generated.

In this paper, we discuss some properties of these default palettes, then go on to propose methods to formulate new ones (in part, programmatically) or validate new proposals. We validate the characteristics of the palettes in part through computing distances between colors in the CIELAB colorspace — to ensure that the colors are easily distinguishable — and in part through testing the colorschemes on actual visualizations.

2 RELATED WORK

A lot of diverse research has been conducted about color. Experiments have shown the importance of considering the size and shape of colored marks for an accurate perception of the data (Stone, 2012; Szafir, 2018). Also, the layout and the number of marks influence how well colors can be perceived (Gramazio et al., 2017). This is especially true if the stimuli are adjacent. Techniques to compensate for contrast effects have been introduced (Mittelstädt et al., 2014) to mitigate negative effects on perceiving neighboring marks.

However, the literature does not focus only on the perception of data values with color. Color naming models were introduced to improve the interaction of analysts with colors (Heer and Stone, 2012). Also, studies have investigated the affect being communicated with colors (Bartram et al., 2017). Independent of the research agenda, it is known that the cultural background (Kim et al., 2019) and the age (Lee et al., 2009) both have an influence on color perception. In our paper, we are not considering the semantics of colors like names or any other confounding factors like age or cultural background.

Based on this aforementioned research, several tools have been proposed to support designers and practitioners in selecting appropriate color ramps to create effective and accessible visual representations: The ColorCat tool, developed by Mittelstädt et al. (Mittelstädt et al., 2015), guides users in the design of colormaps suitable for combined analysis tasks by suggesting colorschemes that accommodate both categorical and continuous data. The Color Thief tool by Dhakar (Dhakar, nd) extracts dominant colors from

Table 1: Palettes included as defaults in d3. The "Total" and "Mean" are distances computed on all the pairwise colors. We report on the mean because, as different palettes have a different number of entries, the total sum of distances can't be compared. The last column, "Min", reports the colors with the minimum distance. Some of the palettes, such as Pastel1 and Pastel2, include colors that are very close together, and would be difficult to distinguish in a visualization.

Name	Total	Mean	Min
Tableau10	298.2	29.8	18.1
Category10	380.1	38	16.2
Observable10	362.5	36.2	18
Set1	389.5	43.2	15.4
Set2	238.4	29.8	16.8
Set3	384.7	32	9.5
Pastel1	180.3	20	6.8
Pastel2	147	18.4	8.7
Paired	461.4	38.4	13.8
Accent	269.1	33.6	21.6
Dark2	281.3	35.2	17.4

images, allowing users to generate color palettes that are directly inspired by specific visual content. Viz Palette, crafted by Lu and Meeks (Lu and Meeks, 2022), assists users in evaluating the usability and aesthetic appeal of color maps in the context of data visualization. Chroma.js, introduced by Aisch (Aisch, nd), provides a comprehensive utility for dynamic color scale generation and manipulation, supporting a variety of color spaces. Adobe Color (Adobe, nd) offers an interactive platform for creating and sharing colorschemes, emphasizing harmonious color combinations based on standard color theory. The Check for Colorblindness tool by Dougherty (Dougherty, 2002) evaluates color palettes for accessibility and ensures visualizations are perceivable by viewers with color vision deficiencies.

While surprisingly little research is dedicated to the aesthetics of color palettes within the visualization domain, Shimizu et al. (Shimizu and Meyer, 2010) introduced the ColorStylingTool, which systematically addresses the aesthetic appearances of colors within the design, helping users create appealing and functional colorschemes. Concurrently, Kita and Myata developed a model that ensures the functionality of color usage while emphasizing aesthetic harmony in visual analytics (Kita and Miyata, 2016). Building on these concepts, the study "Color Aesthetic Enhancement for Categorical Data Visualization" (Lim et al., 2021) proposes methods for visual appeal for categorical data representations, focusing on aesthetic enhancements that do not compromise data legibility. Our findings can be combined with such tools to create a satisfying categorical colorscheme.

In this paper, we restrict ourselves to one-dimensional color ramps. For more information about two-dimensional color maps, we point the interested reader to a survey from Bernard et. al (Bernard et al., 2015).

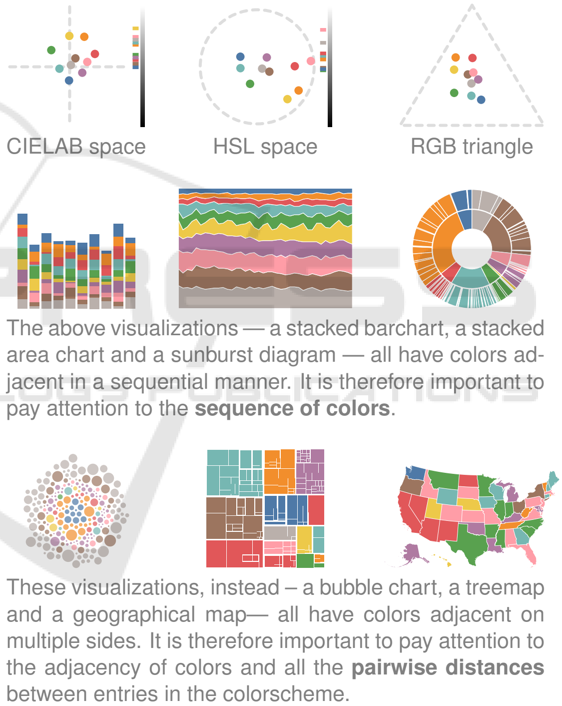


Figure 1: `Tableau10` represented on different colorspaces, and applied to visualizations with different requirements.

3 EXPLORING THE CURRENTLY AVAILABLE COLOR PALETTES

First of all, we take a look at how the colors are represented in different colorspaces to explore the distribution of the selected colors. We selected three colorspaces based on those discussed in previous literature: CIELAB, HSL and RGB. In Figure 1, we can see an example of how these three spaces look on `tableau10`. While RGB and HSL are pretty straightforward methods that most people in visualization know about, CIELAB (Zeileis et al., 2009) is a little more interesting. It is designed to be perceptually uniform, meaning that a change of the same amount in a color value should produce a change of about the same visual importance, which makes it widely used in various industries where color differentiation is critical. The color space includes three axes: L* for lightness, and a* and b* for the color dimensions, where a* represents green to red and b* represents blue to yellow. While all these spaces (RGB, HSL and CIELAB) are 3-dimensional, we chose to represent them projected on a plane, with the third dimension (luminosity) represented on an axis at the side of the representation, inspired by (Stone, 2016) and (Pettiross, 2014).

As a measure of the distance between two colors, then, we use the CIEDE2000 difference, which quantifies the perceived differences between two colors under standard viewing conditions. It improves upon earlier models by better accounting for variations in hue, chroma, and lightness, making it more accurate in aligning with human visual perception. A difference between colors of 1 or 2 is just barely distinguishable, and certainly not viable to distinguish different categories in a visualization. According to Green-Armytage (Green-Armytage, 2006), the minimal pairwise distance for colors to be easily distinguishable is 6.86. However, we can err on the safe side and aim for a minimum larger distance. We can get an idea of how small distances look from table 1.

In order to then actually see the effect that these palettes have when in use, we applied them to sample visualizations, taken from the library of d3 examples (D3 Gallery, nd). We recognize that the use and effect of different palettes depends a lot on the marks used, and their relative positioning in space: while charts such as scatterplots and bubble charts do not have adjacent marks and only use separate areas of color, other charts should take into account the sequentiality of colors in the palette (this is what happens, for instance, in stacked barcharts/area charts — Figure 1).

4 FINDINGS AND RECOMMENDATIONS

Maximizing Distance Between Colors is not Necessarily the Goal: The tableau default color palette went through a redesign in 2016, and the differences in their new default set of colors are detailed in a blog-post on their website (Stone, 2016). The old palette is depicted in Figure 2, while the new palette can be seen in Figure 1.

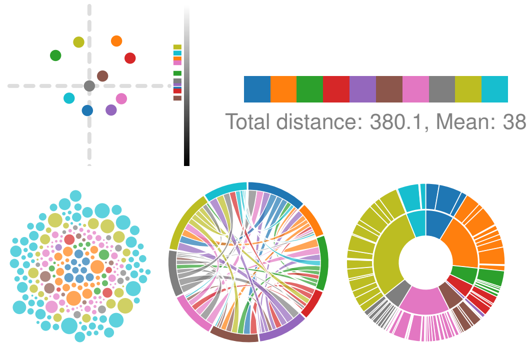


Figure 2: The predecessor palette to `tableau10`, called in d3 `category10`. The figure above contains an illustration of the palette in CIELAB space, with the luminosity shown on a bar to the right of the visualization, then an illustration of all the colors used in it, and three examples of usage in visualizations where the adjacency of colored regions plays with the colors in different ways.

The old palette remains in the set of palettes available in d3, albeit just called `category10`. The interesting thing to note about this change is that in the new one, the colors appear less saturated, but still very distinguishable. Indeed, when represented in CIELAB, all the colors appear closer to the center of the chart in the new iteration. What the designers did here is sacrificing a small amount of vibrancy in the colors to accommodate a more *aesthetically pleasing* set of colors. Now, aesthetically pleasing is a complicated measure to quantify, and the blogpost used to present the new palette does not discuss any metric to quantify such aspect - what the designers did was using their empirical sense of aesthetics to find a minimal movement from the original palette so that the new one could be more pleasing to human eyes, while maintaining high readability.

While some papers about colorscheme optimization try to get colors to be as distanced as possible (Fang et al., 2017), the direction of the redesign of the tableau palette proves that it is not necessary to aim for the maximum distance between colors, and that we can allow for some degree of freedom for distancing colors from their optimal positions.

> *Takeaways:* The maximum distance between colors is not always the best option, and reducing the distance by a minimal amount might improve the aesthetic appeal of the palette.

The Order of Colors Matters: Figure 3 shows

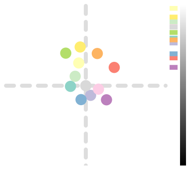
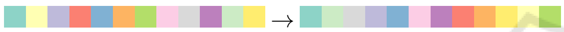


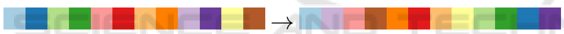
Figure 3: `Set3` in CIELAB.

the `Set3` colorscheme. It is categorized in the d3 colorscheme library as one of the categorical color palettes. This would mean that the colors should have no sequential relationship between them. Which means, the palette should not come close to looking like it has sequential relationships. However, we can trace one line in the CIELAB space so that the colors can be sorted and look like they were extracted from a rainbow colorscheme. Here is a sorting of the colors in the palette that minimizes the distances between one color and the next:



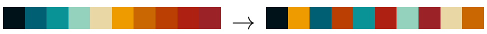
Total distance: 384.7 → Total distance: 217.7

The previously, definitely categorical `Set3` color palette is now looking like a rainbow palette, just through scrambling the colors. This can in part mean that the difference in use classifying a palette as either categorical or sequential also lies in the order in which colors are presented to us. This is another example on the `Paired` colorscheme:



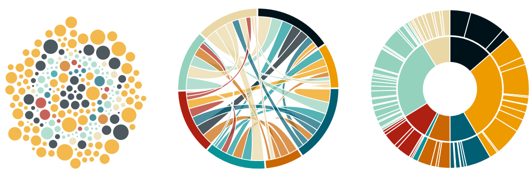
Total distance: 461.4 → Total distance: 295.2

A similar exercise can be repeated the other way around, taking a sequential palette and transforming into a categorical palette by maximizing the distance between subsequent colors:

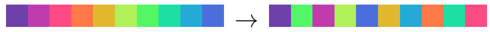


Total distance: 159 → Total distance: 490

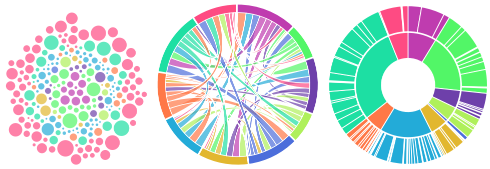
The palette on the left—clearly a sequential one—is presented on the right maximizing the distance between one color and the next. While this still presents a few issues (some colors are too similar), the palette still offers a good amount of very distinguishable colors. If we remove the colors that are too close together to be distinguishable (■ and ■, which have a distance of 7.1), we obtain a viable palette where the minimum distance between colors is 17.1.



This works also on a rainbow colorscheme: the following is generated using d3's interpolateRainbow function.



Total distance: 202.5 → Total distance: 641.5



Taking care of the sequentiality of colors is going to affect mainly visualizations that use color in a sequential way, such as a stacked barchart/area chart. In case the charts do not have this aspect, the palettes need no sorting, but attention should be paid to adjacent areas.

> *Takeaways:* Palettes classified as sequential can be used in place of categorical palettes, but in case we are developing a visualization with a sequential aspect, we should pay attention to color order.

Slicing or Augmenting Palettes to Adapt to a Different Number of Categories: Colorbrewer offers their palettes with a variety of selections of parameters. However, their shorter palettes are just the longer ones, sliced sequentially. The example below shows the Paired palette in the 12 color option, and in the 8 color option, which shows that the shorter version is just the longer, sliced.

Total distance: 461.4 (38.45) Total distance: 250.9 (31.36)

Slicing palettes in this way can lead to sections of the colorspace to become underutilized - meaning that parts of the perceptual colorspace could go underused, and that opportunities for more vibrant and distinguishable colors could be overlooked.

In certain cases we can encounter the opposite problem: we have more categories than the entries in a colorscheme. Because each color must be distinct, there is a practical limit to the number of categories that can be effectively represented before the colors become hard to differentiate (Adobe, for instance, states that it should be 6 at most (Guidelines, nd)). However, cases that require a larger number of categories are always going to exist — one example is the 25-pair color code (pair color code, nd), used in twisted pair wiring for telecommunications. We should thus try to still offer options for such cases, even though they might be not optimal.

> *Takeaways:*
> Palettes should be designed for the amount of colors that they are going to be used with.

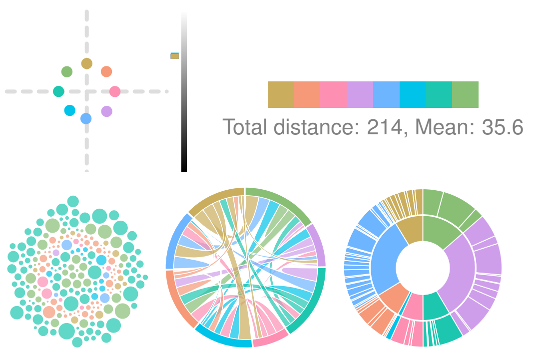
5 CREATING NEW PALETTES

After exploring a few pitfalls and considerations about currently existing color palettes, we discuss some consideration on how to build new palettes that fit the criteria necessary to make a good, properly distinguishable categorical palette. We can take inspiration from already established palettes that were made to be perceptually uniform. Here are a few examples:

Warm from Niccoli's perceptual rainbow (Niccoli, 2013) | Viridis from Van der Welt and Smith (matplotlib (Colormaps, nd)) | CubeHelix from Green (Green, 2011)

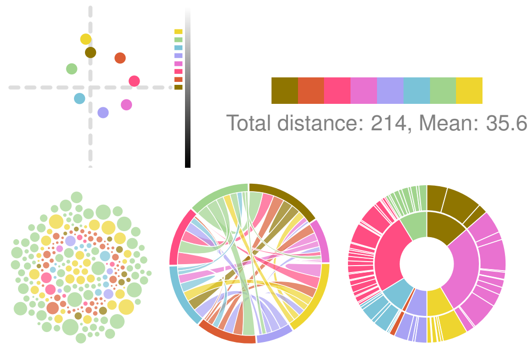
The above palettes are continuous, but show how the colors are designed to attempt to draw an arc of uniform distance in the CIELAB space. This guarantees perceptual uniformity in the colors that compose the palette. The luminosity of the colors is also normally distributed, spanning along the luminosity axis. While the first two — warm and viridis — form arcs, cubehelix goes so far as forming an entire loop, which spans across the entire luminosity axis, which would look like a spiral if seen in three dimensions (Eddins, 2006).

Sampling from an arc and maintaining the same distance from the center of the CIELAB space, we obtain the following:

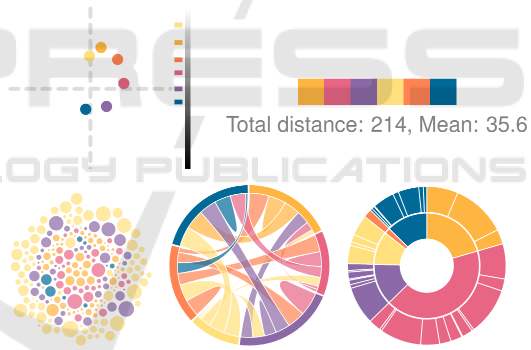


However, this method makes them look muddy—even though the colors are perceptually uniform and nothing stands out more than the others, their complete uniformity might look confusing.

If we also skew the colors on the luminosity axis, as it is done for the continuous palettes above, we obtain a much better effect, where the colors look vibrant and are distinguishable enough:

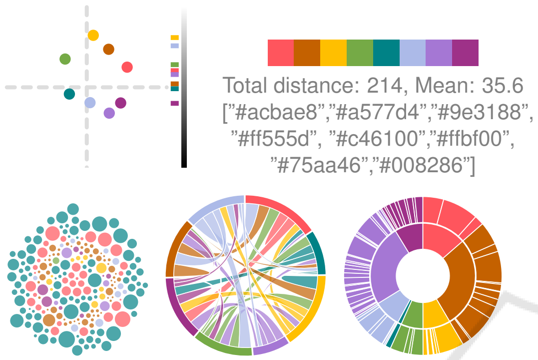


We can also consider the option where we want to exclude a section from the colorspace, such as the case in which we have a colored background and want to avoid shades too similar to it. Here is an example of a 6 color palette that avoids greens:



Overall, sampling colors from spirals or arcs in CIELAB space can produce good results. Maintaining the same distance from the center creates perceptually uniform sets of colors, and sampling the colors across an arc going around the a* and b* axis — in addition to spread in luminosity — produces easily distinguishable colors. Ultimately, what is going to truly make or break a palette are the colors that have the least distance, the ones with a minimum value that is too close in table 1. In the appendix of the paper, we provide a snippet that can be used to test different parameters for generating different colorschemes based on the aforementioned principles. Here is an example of a palette formulated following such methodology:

Figure 4: Formulating palettes by picking and sorting colored pieces of paper can help in the intuitive, creative process. The use of Pantone colors allowed us to match the color with its exact hexadecimal value.



More examples of values and options can be found in the appendix.

We argue for a more creative, intuitive process of building a palette, by simply picking colors according to our own sense of aesthetics, while trying to take careful attention to not include colors that are too similar or too perceptually unbalanced. In fig. 4, we show an attempt at creating one by arranging Pantone cards. The same principles used to craft palettes, explained in the previous paragraphs, can also be used to test empirically-formulated palettes — after formulating one, we can use distances and charts to check that we avoided pitfalls and have a balanced palette. Although a solution based on precise algorithms would be the preferable solution for the task, all the most common palettes are formulated through a creative design process, as documented in the colorbrewer paper (Harrower and Brewer, 2003), the tableau blog (Stone, 2016), and, recently, the description of the design process to formulate the `observable10` colorscheme (Pettiross, 2014).

6 LIMITATIONS AND FUTURE WORK

This work is nothing but a speck of dust within the research about categorical color palettes, and more than anything else, *a call for more creativity and freedom in categorical color choices in visualization*.

The space of viable research is enormous, and is subject to ample use and exploration. Here are a few **limitations of this paper:** We are currently setting aside any *semantic meaning* of the underlying data, or *cultural influences* that might appear on color perception, and focusing exclusively on objectively separable colors. While certainly an incredibly interesting field of study, we believe it would need a much more in-depth exploration, that we set aside for space reasons of this short paper. We also did not discuss nearly enough the *accessibility* of the colorschemes for people with color vision deficiencies — which should be taken into account and it is a frequently discussed topic in visualization research (Geissbuehler and Lasser, 2013). Visualizations of the colorschemes in other spaces are also an option that should be explored (such as CIECAM02 (Li et al., 2000)). Finally, we should also take into account how colors interact with the rest of the context they are inserted in: the *background color* of a visualization, for instance, can have a relevant effect on how colors stand out from one another.

This is **preliminary work** towards an investigation on how color is used in visualization. We already started to analyze the use of categorical colorschemes in vis papers, analyzing what colorschemes and what choices are made in combination with the tasks supported by the visualizations, and we plan to use this preliminary work to compare the findings of this new investigation in a future submission.

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