

Tree Colors: color schemes for tree structured data

Martijn Tennekes and Edwin de Jonge

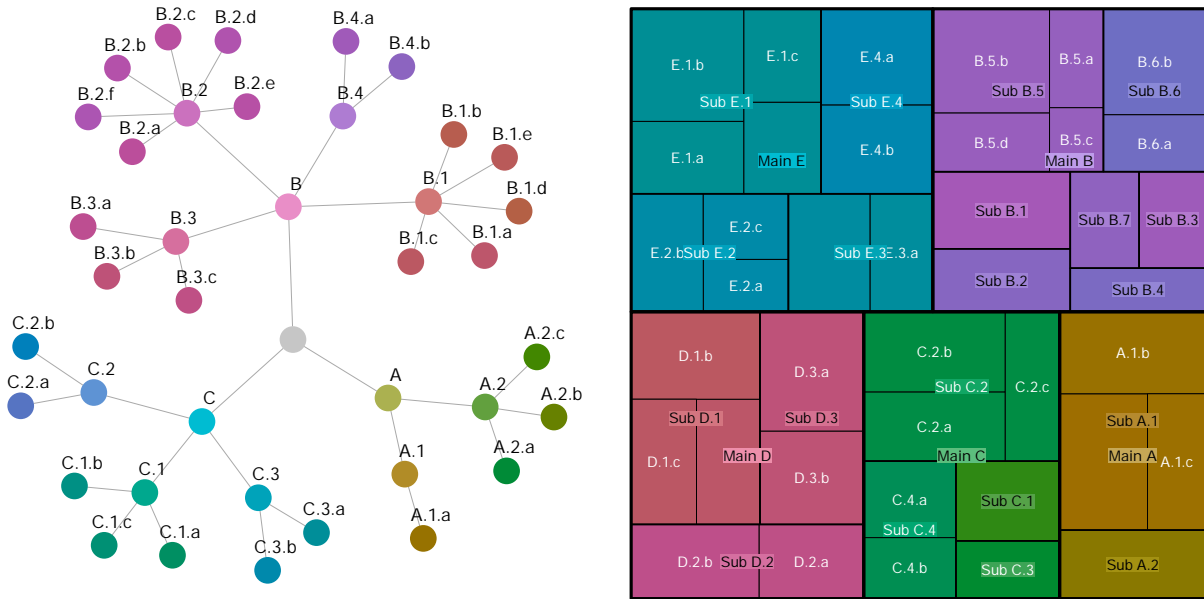


Fig. 1. Tree Colors applied to a directed graph (left) and a treemap (right).

Abstract— We present a method to map tree structures to colors from the Hue-Chroma-Luminance color model, which is known for its well balanced perceptual properties. The Tree Colors method can be tuned with several parameters, which influence on the resulting color palette is discussed in detail. We provide a free and open source implementation with sensible parameter defaults. Categorical data are very common in statistical graphics, and often these categories form a classification tree. We evaluate applying Tree Colors to tree structured data with a survey on a large group of users from a national statistical institute. Our user study suggests that tree color schemes are very useful, not only for improving standard hierarchical visualizations such as treemaps and graphs, but also for unveiling tree structure in non-hierarchical visualizations.

Index Terms—Color palettes, statistical graphics, hierarchical data.

1 INTRODUCTION

Data are often hierarchically structured in official statistics. Business data are typically broken down by economic activity and demographic data by geographic region. To produce statistics it is therefore important to expose rough input data without losing the underlying hierarchical structure. Several data visualization methods are useful for this task, for instance treemaps [16, 18]. Color palettes reflecting the hierarchical structure would be very useful in supporting visual analysis.

Assigning colors to categories is far from trivial. On the one hand, qualitative colors should be distinct, but on the other hand they should not suggest non-existent order or proximity and introduce perceptual bias. The selection of color palettes for categorical data first depends on the type of data. For nominal data, such as gender or nationality, qualitative color palettes are used, while for ordinal data, such as level of urbanization, sequential or diverging palettes are used [2, 21]. However, for hierarchical categories there are no specific guidelines

for selecting color palettes, to the best of our knowledge.

Although many tree visualizations are proposed in literature [15], most of them use color to a small extent. A visualization technique that uses color as a major attribute is the InterRing [20], a navigation tool with a radial layout. The leaf nodes are assigned to a different hue values. The color of a parent node is derived from averaging the colors of its children, where larger branches have more weight. An implicit effect is that colors of higher hierarchical levels are less saturated, except for one-child-per-parent branches. Hierarchical color schemes are also applied to the Hyperbolic Wheel [10], an exploration tool for hierarchical data. These color schemes are abstracted from the Hue-Saturation-Lightness (HSL) space, where brightness decreases proportional from root to leaf nodes, and where child nodes inherit the hue values from their parent nodes and add small hue values to distinct them from their siblings. However, hue values of nodes in the same hierarchical layer may be overlapping.

Our purpose is to map tree structures to color palettes with the following three properties. First, the hierarchical depth of a node should be perceived with color. The second property is that branches should be clearly distinguishable in all parts of the tree, or at least the main branches in large trees. Third and last, each node should have a unique color that is also perceived as unique as much as possible.

The color palettes that are obtained by our proposed method are called Tree Colors. As a starting point, we use the Hue-Chroma-

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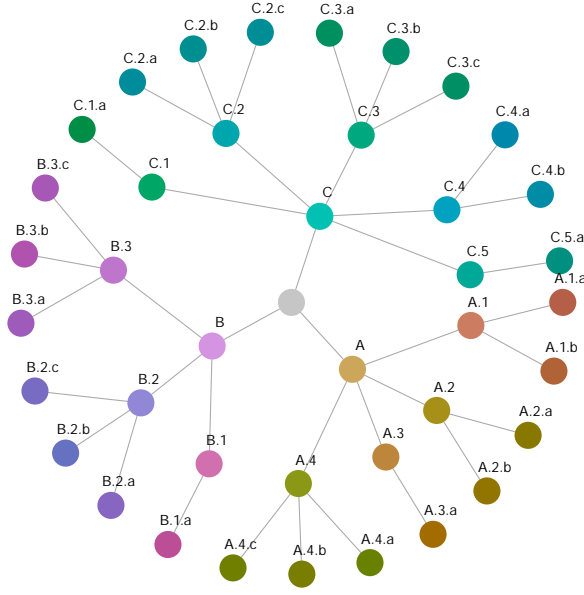


Fig. 2. Radial graph with Tree Colors.

Luminance (HCL) space, a transformation of the CIELUV color space, that is designed with the aim to control human color perception [7]. Colors with different hue values are perceptually uniform in colorfulness and brightness, which does not hold for the popular Hue-Saturation-Value (HSV) and HSL color spaces [21].

This paper is outlined as follows. In Section 2 we describe the proposed method. We provide several applications of statistical graphics that use Tree Colors in Section 4. The conducted user survey to evaluate the method is described in Section 5. We conclude with a discussion in Section 6.

2 METHOD

Our method maps a tree structure on colors in HCL space, such that it reflects the hierarchical properties of the tree. We use the hue parameter H , with range $[0, 360]$, for the tree structure, where the hue of each child node resembles the hue of its parent. The chroma and luminance parameters C and L , both with range $[0, 100]$, are used to discriminate the different hierarchical levels.

We illustrate Tree Colors with a radial tree graph that is depicted in Figure 2. Although other graph layouts may be more suitable to highlight the tree structure, for instance the Fruchterman-Reingold algorithm [6] applied in the graph in Figure 1, the applied radial Reingold-Tilford layout [13] preserves the original order of nodes in each hierarchical layer, which is in many cases, and also in this case, purely alphabetical. The Tree Colors in this graph can therefore be applied in the same order in any other visualization method with a radial layout, or a layer-wise linear layout.

2.1 Hue values

For selecting hue values we use the following recursive algorithm. It will assign to each node v of a tree structure a hue value H and a hue value range r . We start with the root node, which has by default hue range $[H_{start} = 0, H_{end} = 360]$:

AssignHue(v, r)

1. Assign the middle hue value in r to the hue value of node v , which is H_v ¹.
2. Let N be the number of child nodes of v . If $N > 0$:
 - i divide r in N equal parts r_i with $i = 1, \dots, N$;

¹The root node itself is colored grey, so its hue is irrelevant.

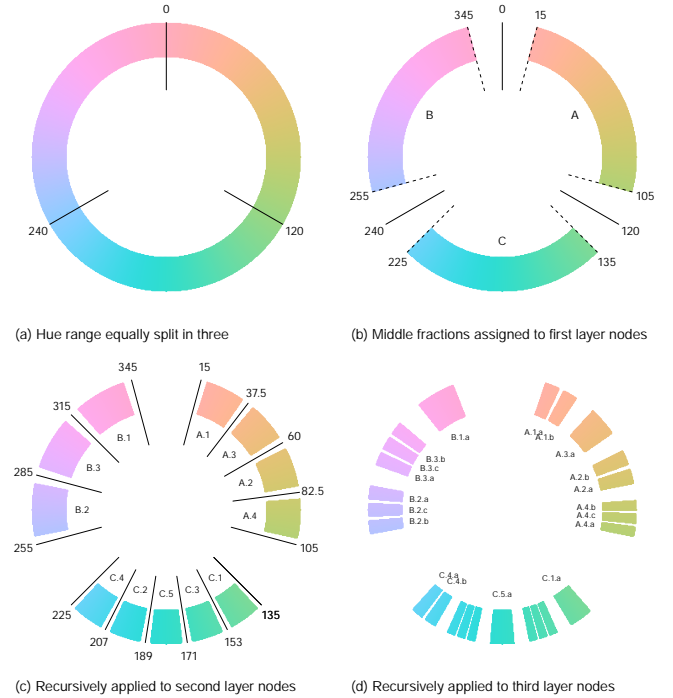


Fig. 3. Assignment of hue values.

- ii if H_{perm} then permute the r_i 's;
- iii if H_{rev} then reverse the even-numbered r_i 's;
- iv reduce each r_i by keeping the middle fraction H_{frac} ;
- v for each child node v_i DO AssignHue(v_i, r_i).

This algorithm is illustrated in Figure 3. In (a) the full hue range (for a constant $C = 60$ and $L = 70$) is split in three equal parts, since the root node has three children. Of each part, only the middle fractions (with $H_{frac} = 0.75$ by default) are kept in (b). The ranges are assigned to A, B, and C. In (c) and (d) these steps are recursively taken for the deepest two hierarchical layers.

2.1.1 Hue permutations and reversals

In many hierarchical structures, there is no order between siblings. When the nodes in such structure are plotted in a linear or radial layout, the colors of the siblings should not introduce a perceptual order. Therefore, the assigned hue ranges are by default ($H_{perm} = \text{TRUE}$) permuted among the siblings. The used permutation order is based on the five-elements-permutation $[1, 3, 5, 2, 4]$. The way to determine the permuted order is to equally spread the siblings on a circle in the original order, and to pick the siblings at angles of 0 modulo 144 degrees. Notice that the difference of any two adjacent siblings in $[1, 3, 5, 2, 4]$ is exactly $2/5 * 360 = 144$ degrees, also between the last and the first sibling. For the cases with more than five siblings this picking angle is rounded down if needed. It may occur that a sibling is picked twice while others have not yet been picked, for instance when 360 is a multiple of the rounded picking angle. In these cases, the next sibling is picked and the process continues with the same picking angle. For the three and four siblings case we use the permutations $[1, 3, 2]$ and $[1, 3, 2, 4]$ respectively.

The permutations for three to twelve siblings for a hue range between 120 (green) and 240 (blue) are depicted in Figure 4. Note that the order of the five-siblings case, which is $[1, 3, 5, 2, 4]$, is the position of the siblings A, B, C, D, and E respectively. Therefore, the permutation of them is A, D, B, E, and C.

Furthermore, the permuted color ranges within even numbered branches are by default reversed ($H_{rev} = \text{TRUE}$) to differentiate between branches. This is needed because the first category is always

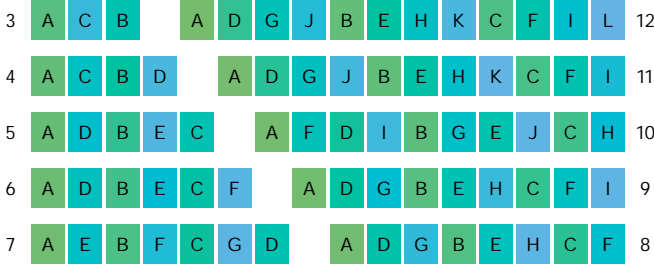


Fig. 4. Purmutations of siblings.

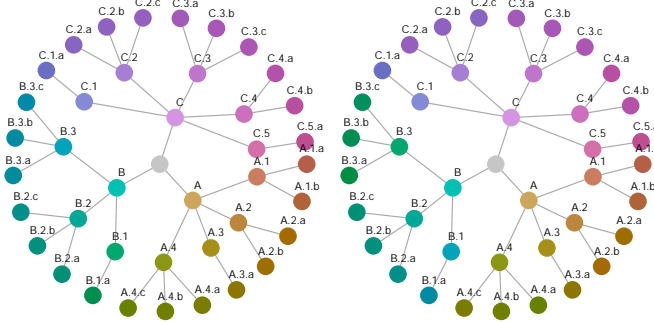


Fig. 5. Radial graphs with permutation disabled. Reversal of even-numbered branches is disabled on the left, and enabled on the right.

mapped to the lowest hue value (in Figure 4, category A has the most greenish color in all shown cases), and the last category to a higher hue value. To reverse the hue ranges in an alternating way, so only the even-numbered, the hue distance between any two adjacent nodes with different parents will increase, and thus easier to tell apart.

Note that the labeling in Figure 3 shows that the assignment of colors is permuted and also reversed for even-numbered branches. The three top-layer hue ranges $[0, 120]$, $[120, 240]$, and $[240, 360]$ are assigned to A, C, and B respectively. Branches A and C are odd-numbered, so the hue ranges of the second layer are only permuted; the permutations for these branches are $[A.1, A.3, A.2, A.4]$, and $[C.1, C.3, C.5, C.2, C.4]$. Since branch B is odd-numbered, the hue ranges are not only permuted, but also reversed: $[B.2, B.3, B.1]$.

The result of these permutations is that siblings are discriminated in each hierarchical layer, which is illustrated in Figure 2. For comparison, the permutation is turned off in the graphs shown in Figure 5. In the left graph, the hue values form a gradual hue circle, where only the hue fraction H_{frac} creates small hue gaps between branches. The even-numbered branches are reversed in the right graph. The leaf nodes of branch B are now more distinct from the other leaf nodes. However, the distinction between branches of the second hierarchical layer is still less than with permutation enabled (Figure 2).

2.1.2 Hue fraction

The fraction H_{frac} is needed to introduce a ‘hue gap’ between nodes with a different parent. This choice is a trade-off between discriminating different main branches and discriminating different leaf nodes. If $H_{frac} = 0$, the hue ranges are diminished to single hue points, which implies that each main branch is assigned a constant hue. On the other end of the extreme, if $H_{frac} = 1$, the full hue range is available at each hierarchical layer, which makes leaf nodes easier to distinguish, but harder to take apart from leaf nodes of other branches.

The choice of f depends on several aspects, such as the application, the size and dimensions of the hierarchical data, and on the used visualization method. In Figures 6 a graph with a Fruchterman-Reingold

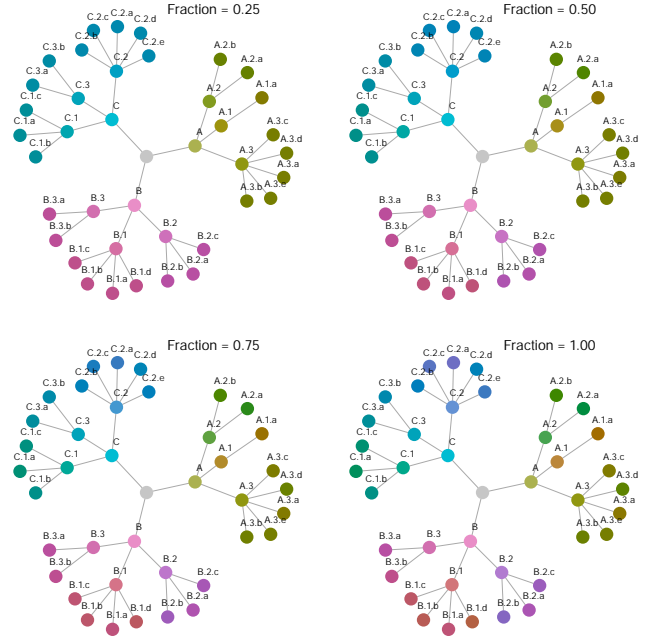


Fig. 6. Graphs with different fraction values.

layout [6] is shown with different values of H_{frac} . For such explicit tree visualizations, high values of H_{frac} can be chosen to discriminate the leaf nodes without loosing touch of the global tree structure which is clearly visible, also without Tree Colors. Even values of (or close to) 1.00 are appropriate here. To be on the save side, we suggest $H_{frac} = 0.75$ for explicit tree visualizations as a guideline.

For implicit tree visualizations where the tree structure is not clearly visible without colors, lower values of H_{frac} are more suitable. To illustrate this, a treemap with different values of H_{frac} is depicted in Figure 7. We applied the ordered treemap layout [1] for these treemaps. For $H_{frac} = 0.75$ and especially $H_{frac} = 1.00$, it is difficult to grasp the global tree structure immediately; the main categories A and C are hard to take apart as well as the categories B and D. Therefore we suggest $H_{frac} = 0.50$ as a rule of thumb for implicit tree visualizations.

2.2 Chroma and luminance values

In order to show depth in the tree, we use bright colors for nodes high in the tree and dark colors for nodes lower in the tree. The intuition behind this approach is that dark colors are often associated by humans with high particle densities. In most tree representations, the density of nodes will increase with the depth of the tree. Therefore, we let luminance decrease linearly with depth. We set the default luminance value for the first (highest) layer below the root as $L_1 = 70$. For the other layers $i = 2, \dots, d$, where d is the depth of the tree, the luminance value is defined as

$$L_i = (i - 1)\beta^L + L_1, \quad (1)$$

where the default value for the slope parameter β^L is set to -10 . In case the root node is visualized, it is colored grey. Its luminance value is specified by $L_0 = L_1 - \beta^L$.

In Figure 8 a table of colors are depicted for various chroma and luminance values and a constant hue of $H = 300$. Brighter colors (with higher values of L) have the tendency to become too saturated in our opinion, for instance, the colors with $L = 70$ and $C \geq 70$. However, for dark colors, high values of C may help to discriminate them distinguish them from other dark colors with different hue values. The question therefore is, what values of C are needed for what values of L in order to distinguish the colors easily without using too much saturation.



Fig. 7. Treemaps with different fraction values.

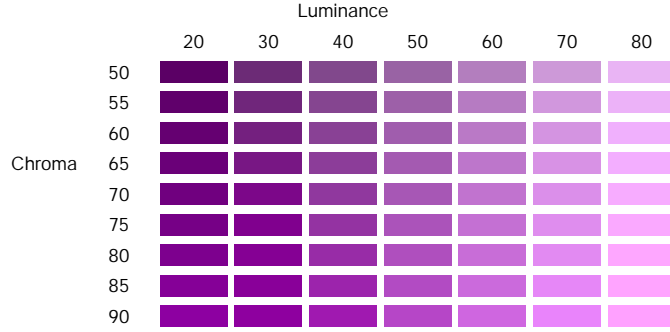


Fig. 8. Colors for different L and C values with a constant $H = 300$.

For different pairs of C and L , color palettes with a fixed hue range from 120 and 360 are depicted in Figure 9. Among the bright color palettes (with $L = 70$) the saturation level of $C = 60$ is sufficient to discriminate the colors easily. For the dark color palettes (with $L = 30$), saturation values of $C = 80$ or higher are not superfluous, especially because the assigned hue range is often very narrow for nodes low in the tree.

Therefore, we propose to increase C with depth. Let $C_1 = 60$ be the chroma value for the first layer. For layer $i = 2, \dots, d$ the chroma value is defined as

$$C_i = (i - 1)\beta^C + C_1, \quad (2)$$

where the slope parameter is set to $\beta^C = 5$ by default. The chroma value for the root node is irrelevant, since it is colored grey.

So per hierarchical layer i , we have specified a fixed pair of L_i and C_i . For these pairs, we depicted color palettes with a fixed hue range between 120 and 360 in Figure 10.

2.3 Parameter overview

An overview of all parameters that are used in the described method is provided in Table 1. The luminance and chroma parameters are restricted to the following constraints:

$$0 \leq (d - 1)\beta^L + L_1 \leq 100 \quad (3)$$

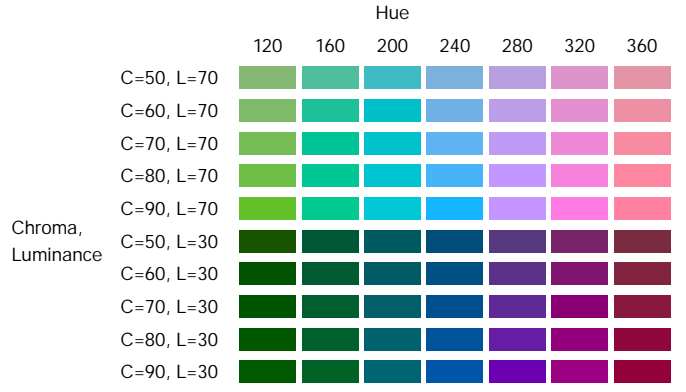


Fig. 9. Colors palettes for different pairs of L and C .

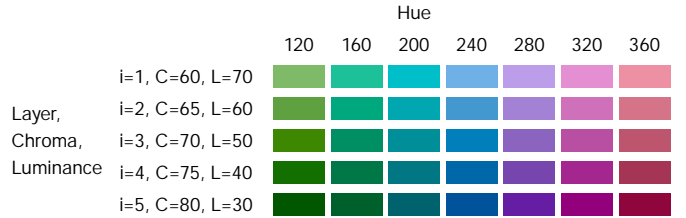


Fig. 10. Colors palettes for matched pairs of default L and C values for the top five hierarchical layers.

and

$$0 \leq (d - 1)\beta^C + C_1 \leq 100. \quad (4)$$

3 SOFTWARE

The Tree Colors are implemented in the treemap package [17] of the statistical software environment R [12]. All treemaps in this paper are created directly with this package, without post-processing. The implemented layout algorithms are the ordered treemap layout algorithm (pivot by size) [1] and the squarified treemap layout algorithm [3]. By default, Tree Colors are used to clarify the hierarchical structure of the data. However, the color attribute can also be used for a second variable or to compare two hierarchical datasets [18].

The graphs in this paper are also created with the treemap package. The graph layouts are processed with the dependency package igraph [4].

The treemap package also contains an interactive tool to create and visualize Tree Colors. After installation R and the package treemap, only two lines of code are required to start this tool:

```
library ( treemap )
treecolors ( )
```

Parameter		Range	Default value
Hue start	H_{start}	0 to 360	0
Hue end	H_{end}	0 to 360	360
Hue fraction	H_f	0 to 1	0.75 (explicit) 0.50 (implicit)
Hue permutations	H_{perm}	Boolean	TRUE
Hue reverse	H_{rev}	Boolean	TRUE
Luminance first level value	L_1	0 to 100	70
Luminance slope value	β^L		-10
Chroma first level value	C_1	0 to 100	60
Chroma slope value	β^C		5

Table 1. Parameters

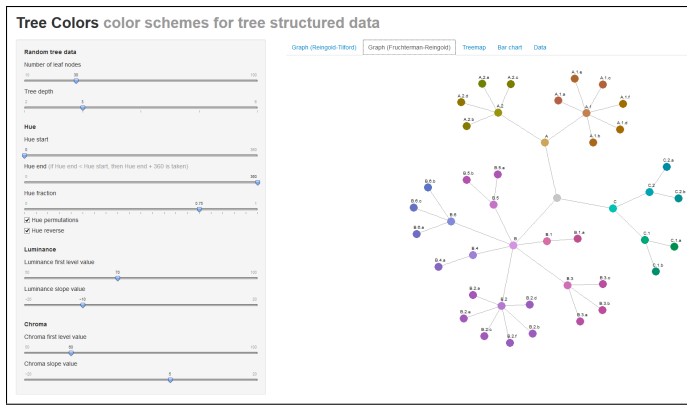


Fig. 11. Screenshot.

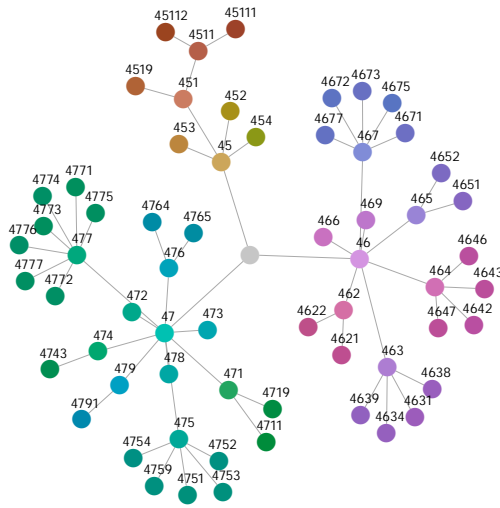


Fig. 12. Graph of all wholesale and retail trade NACE codes produced by the Fruchterman-Reingold layout algorithm

A screenshot of this interactive tool is shown in Figure 11. On the leftside panel, the user can create random tree data, and experiment with the parameters. On the main panel, four visualizations can be shown: two graphs (Reingold-Tilford and Fruchterman-Reingold), a treemap and a bar chart. Also a table of the tree structured data is provided included the color values in hexadecimal format and the HCL values of the all nodes.

4 APPLICATIONS

4.1 Economic activity

National statistics on business enterprises are often published per economic sector. Economic sectors are typically structured hierarchically. For instance, the class of bakeries may have a parent class food manufacturers, which in turn is a child of the class of manufacturers. All member states of the European Union use same classification system of economic activity, namely the *Nomenclature statistique des activités économiques dans la Communauté européenne* (NACE) system [5]. This system has 21 main economic sectors and consists of four hierarchical layers.

In Figure 12, the NACE codes of the sector G, wholesale and retail trade, are depicted by a graph with the Fruchterman-Reingold layout algorithm [6]. In our opinion, Tree Colors contribute to clarify the tree structure.

The same graph is depicted in Figure 13 with the Kamada-Kawai layout algorithm [9]. In comparison to the Figure 12, the leaf nodes are all forced more outwards by the Kamada-Kawai algorithm. This may

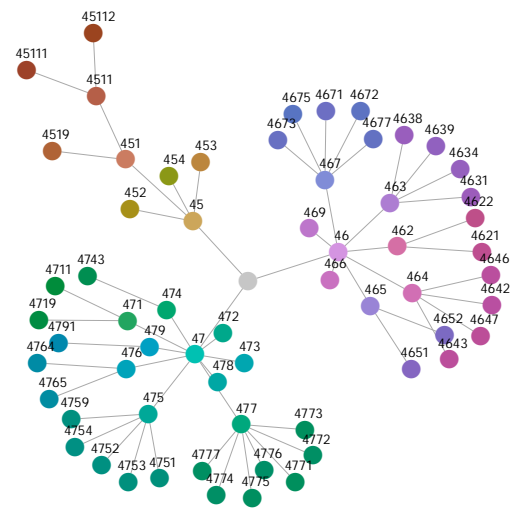


Fig. 13. Graph of all wholesale and retail trade NACE codes produced by the Kamada-Kawai layout algorithm

clarify the tree structure better, but at the cost of possible artifacts. In this case there are the two crossed edges, namely 465-4651 and 464-4643. The Tree Colors of the corresponding nodes help to discriminate the two local branches that overlap each other.

One of the largest statistics that uses the NACE system are the Structural Business Statistics (SBS) that cover industry, construction, trade and services. The main target variables are turnover, number of persons employed, total purchases, and financial result. These statistics are produced for the entire European Union. However, the applied production method which include data collection, editing, analyses and estimation may vary from country to country, depending on the budget, legislation, and the availability of administrative data sources such as tax data and the chamber of commerce. As for the Netherlands, data from small enterprises, i.e. less than 10 employees, are taken directly from tax administrations, data from medium enterprises (up to 50 employees) are taken from a sample survey, and data from large enterprises (50 employees or more) are taken from a full sample survey [14].

In Figure 14, the net turnover of the Dutch wholesale and retail trade enterprises in 2011 is visualized by a treemap. The Tree Colors of the non-leaf nodes are used for the text label backgrounds. The number of digits in the category names represent the hierarchical layer. Each of the three main branches of this sector (45, 46 and 47) clearly has a distinct hue range. Furthermore, some leaf nodes, for instance the pink colored 466, are a brighter than others, because they represent the third rather than the fourth NACE layer.

4.2 Regional classifications

Many publications in official statistics are broken down by region, especially regarding demographics. In many situations, thematic maps are useful as a data visualization tool for spatial statistics, in particular choropleths and cartograms. However, non-spatial visualization methods are often sufficient for the task at hand. In those cases, the geographic location of the regions is less important for the analysis than the comparison of some specific target variable between regions. Tree Colors can improve the discrimination between the regions in a subtle way.

In Figure 15 a bar chart created with the R package ggplot2 [19] is depicted of the Dutch population broken down by its twelve provinces. For comparing the populations to each other, a bar chart is a good working horse, since length is perceived quite accurately [11]. We applied Tree Colors to add information about the geographic location of the provinces. Typically, the provinces are grouped by the country parts north, east, west, and south. We use those country parts as the

Method	Color scheme	Version 1	Version 2
Graph	Main Branch Colors	Dataset 1	Dataset 2
Graph	Tree Colors	Dataset 2	Dataset 1
Treemap	Tree Colors	Dataset 3	Dataset 4
Treemap	Main Branch Colors	Dataset 4	Dataset 3
Bar chart	Main Branch Colors	Dataset 5	Dataset 6
Bar chart	Tree Colors	Dataset 6	Dataset 5

Table 2. Overview of charts in the survey

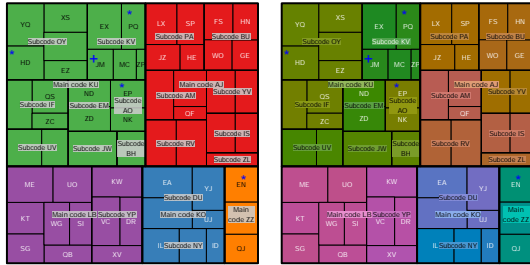


Fig. 17. Treemaps applied to Dataset 4 with Main Branch Colors (left) and Tree Colors (right)

the data structure point of view, we considered the last code as the correct answer.

Offspring How many subcodes does main branch X have? This was an open question.

Help What do you think of the following statement? The charts colors helped me to answer the question(s) above. This question is a five-level Likert item with the answer options Strongly disagree (SD), Disagree (D), Neutral (N), Agree (A) and Strongly agree (SA).

Per visualization method, respondents were asked those reading questions for two plots of different datasets, one with Main Branch Colors and one with Tree Colors.

Next, respondents were asked to evaluate these two plots with three questions:

Prettiness Which chart is the prettiest?

Interpretation Which colors contributed most in interpreting the chart?

Overview Which colors provided the best overview?

Finally, respondent were given the possibility to write down comments or suggestions.

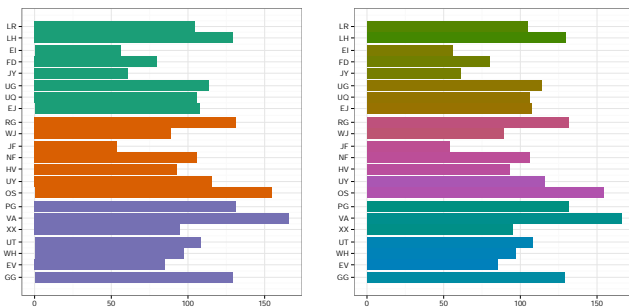


Fig. 18. Bar charts applied to Dataset 5 with Main Branch Colors (left) and Tree Colors (right)

5.2 User survey results

We recruited 95 respondents with normal color vision and 10 respondents with a color vision deficiency.

The results of the reading questions are summarized in the left part of Figure 19. Per dataset the percentages of correct answers, that is, from a data structure point of view, are depicted as orange points for the Main Branch Colors and as green points for the Tree Colors. For each percentage, the corresponding 95% confidence interval is depicted as a line. The right part of Figure 19 shows per visualization method the distribution of answers to the question whether colors helped in answering the reading questions.

Of all three visualization methods, the reading questions regarding the graphs received the highest percentages of correct answers for both color schemes. The reason is the questions are fairly easy to answer by the explicit tree layouts of graphs. The Tree Colors score slightly better on the relationship questions. The questions about the offspring resulted in 100% scores for all four color scheme - dataset combinations. As for the graphs, respondents experienced more help from Tree Colors than from Main Branch Colors.

The percentages of correct answers for the treemaps were lower than for the graphs. It turned out the many respondents also took into account other aesthetics of the rectangles, in particular shape (aspect ratio) and area size, for answering the questions. The Tree Colors scored better the Main Branch Colors on the relationship question for Dataset 3. However, the scores on this question were identical for Dataset 4. This difference may be caused by the different color scheme instances that were applied. The Main Branch Colors scored better than the Tree Colors on the questions about the number of subcodes. A possible explanation of this result could be that respondents clustered the subcode colors by hue. For instance, for Figure 17(left) respondents were asked how many subcodes Main code AJ has. The correct answer is 7, while one out of four respondents thought the correct answer is 5. Probably, respondents considered subcodes PA and BU to be part of a different main code than the other 5 subcodes. The amount of help that respondents got from the applied colors was similar for Tree Colors and Main Branch Colors.

As for the bar charts, the majority of the respondents did not observe the underlying data hierarchy when the Main Branch Colors were applied. Obviously, the spacings between the bars did not stand out clearly in comparison to other aesthetics such as color and length. For example, the question that belongs to Figure ??(left) was which code or codes are most similar to UT, where the possible answers are NF, XX, EV, and GG. Almost 51% of the respondents checked the codes that belong to the same main branch, XX, EV and GG, and therefore only used color to answer the question. Another 27% only used length to answer the question, since they answered NF. Only 4% of the respondents answered EV, which is given the data hierarchy the correct answer. When Tree Colors were applied, see Figure 18(right), none of the respondents checked XX, EV and GG, 23% chose the equal-length bar NF, and 63% answered EV correctly. By the broadly defined question, it would be a very weak argument to claim the success of Tree Colors on this large difference. However, in our opinion it does indicate that Tree Colors are a valuable attribute to visualize a hierarchical data structure in non-hierarchical plots such as bar charts, line charts, and area charts.

The evaluation questions are summarized in Figure 20. In general, respondents liked both color schemes equally, where Tree Colors were favored for graphs.

The interpretation of the graphs was experienced easier with Tree Colors except for the treemaps. This could be explained by level of difficulty of the visualization methods. Both graph and bar chart are easy to read visualization methods that the vast majority of the respondents are familiar with. Therefore, people are able to see the benefits of the additional information that the Tree Colors provide over Main Branch Colors. However, treemaps are still largely unknown by the respondents. Additional information provided by the applied color scheme could therefore be a little confusing.

The charts with Main Branch Colors provided the best overview

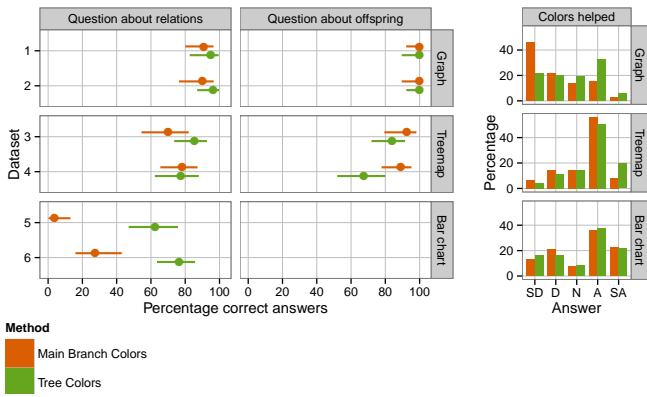


Fig. 19. Results of reading questions

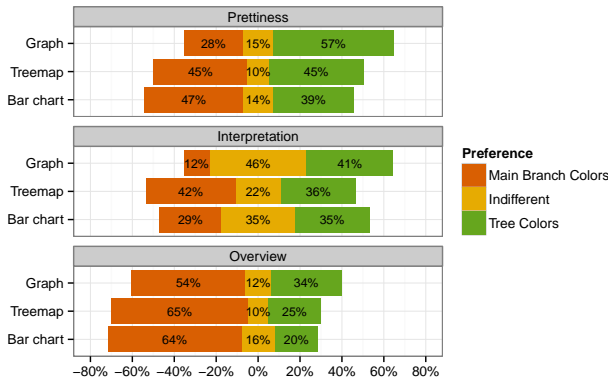


Fig. 20. Results of evaluation questions

for the majority of the respondents. This result is not surprising at all, since a good overview is obtained by discriminating the main branches. Recall that the hue fraction, H_f , is a trade-off between discrimination of the main branched and discrimination of the leaf nodes. Notice that Tree Colors with $H_f = 0$ are identical to Main Branch Colors, where only the applied color palette is different.

6 DISCUSSION

ACKNOWLEDGMENTS

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