Colored Mosaic Matrix: Visualization Technique for High-Dimensional Data

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***Abstract*—Owing to a limited display resolution, it may be difficult to obtain an overview of high-dimensional data in the display area used for visualization. In this paper, we aimed to obtain an overview of high-dimensional data in a limited screen area. We developed Colored Mosaic Matrix as a method to obtain a data overview. Colored Mosaic Matrix is a visualization method for high-dimensional categorical data that uses a color representation of the features. By representing quantitative data in category units, the proposed method enables the visualization of data containing a large number of records. As a result of an experimental investigation of its readability, we found our method to be useful in obtaining a data overview.**

***Keywords*-High-Dimensional Data; Color Representation; Panel Matrix**

I. Introduction

Visualization is a very effective method for extracting knowledge from data and helping with our understanding of human intuition. Therefore, data visualization is a useful analysis tool. Much of the data appearing in various areas are multi-dimensional data having more than one dimension. To analyze such multi-dimensional data, various visualization techniques have been developed. For example, Scatterplot Matrix [1] is a technique used to display a matrix arranged scatterplot in pair of all dimensions that can be combined. The dimensions are aligned regularly so that it is easy to search for the required dimension during an analysis. On the other hand, there is a physical limit to the size of the screen. In visualizing high-dimensional data, obtaining an overview of all dimensions is therefore difficult.

By increasing the resolution itself using a large-screen display, it is possible to visualize all dimensions at the same time. However, the larger the display used for visualization, the larger the area that must be looked at, and the longer the distance for the line of sight needed for an analysis. To conduct a smooth analysis, it is therefore desirable to use a common desktop display.

We aim to display an overview of high-dimensional data on a full HD-resolution (1920×1080) display. In particular, we target the high-dimensional data of 30 or more dimensions, which are difficult to treat. To analyze high-dimensional data from an overview, we intend to maintain a high readability and increase the number of dimensions that can be displayed in a limited drawing area.

Our contributions are as follows. First, we developed a method to browse an overview of high-dimensional data instantaneously. By using colors, it becomes possible to read the features of data in a narrower area. Second, in our experiment, we evaluated the relationship between the drawing area and the readability quantitatively.

II. Related Work

A. Panel Matrix

Panel Matrix involves two-dimensional pair-wise plots of adjacent variates. Scatterplot Matrix [1] arranges the scatter plots of all possible combinations of dimensions to display all of the multi-dimensional data required. In addition, SCATTERDICE [2] is a visualization technique that extends Scatterplot Matrix. By operating interactively, like the roll of a dice, SCATTERDICE achieves the task of switching between dimensions in multi-dimensional data. Intuitive dimensional switching supports an analysis of data consisting of a large number of dimensions. However, when using these methods to represent all high-dimensional data instantaneously, each Scatterplot drawing area becomes narrower. Over-plotting then occurs by increasing the number of points per unit area. When over-plotting occurs, the data analysis becomes more difficult.

Mosaic Plot [3] is a technique for a space-filling visualization of multi-dimensional categorical data. The drawing area is divided into rectangles whose area depends on the ratio of the category. Mosaic Matrix [4] is a *Panel Matrix* visualization technique. Like Scatterplot Matrix, Mosaic Matrix is displayed in a matrix form of Mosaic Plots. However, for an increased number of data dimensions, it becomes difficult to distinguish between each rectangle in a small Mosaic Plot.

B. Non-Cartesian Displays

Non-Cartesian Displays map data into non-Cartesian axes. Parallel Coordinates Plot (PCP) [5], [6] is a kind of *Non-Cartesian Displays*, and is a multi-dimensional data visualization method using parallel coordinates. In a typical PCP,

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a direct comparison can be performed only between adjacent dimensions. Furthermore, the width of the axis becomes narrow, which decreases the readability. By arranging multiple PCP vertically, Heinrich et al. [7] developed a method to display adjacent pairs of all dimensions. Because dimensions are not arranged regularly, it is difficult to explore arbitrary dimensional pairs in this type of visualization.

One countermeasure against over-plotting is to display only part of the data dimensions. Sips et al. [8] developed a method using dimensional sorting by distance and entropy to display only the useful part of an analysis. VisBricks [9] represents data by allowing the dimension and records that the user wants to view to be selected. When dealing with high-dimensional data in these techniques, it is difficult to determine the part of the data to be visualized. For example, problems arise, such as how much data should be displayed, or how to determine the necessary part of the data for analysis.

RadViz [10], [11] represents high-dimensional data by placing dimensions on the circumference of a 2D drawing area. In RadViz, it is difficult to read the numerical values of each dimension directly. Moreover, the representation itself may cause the data to be misread.

C. Representation of Density and Distribution Using Colors

As a means to improve the readability in a narrow region, it is effective to use a color representation. Visualization techniques using color [12], [13] have been developed to represent the density of data. However, these techniques are unsuitable in a narrow area because they represent the data distribution based on the position of the colors.

Two-Tone Pseudo Coloring [14] is a technique for representing data of only one-dimensional distribution using colors. While this is not a multi-dimensional data visualization technique, it is possible to read the data features using a thin and small rectangular area.

III. Visual Representation

A. Design Principles of Representation

The basic principle of seeking information can be summarized as follows: *Overview first, zoom and filter, then details-on-demand* [15]. Even when analyzing high-dimensional data, it is desirable that the data overview be obtained first. To obtain the data overview intuitively, we designed a method to visualize all dimensions at once. When displaying all high-dimensional data at the same time, the readability is reduced through over-plotting. Therefore, we use a drawing method with good space efficiency.

We focused on a space-filling visualization method, and developed a technique that can obtain an overview of high-dimensional data. Quantitative data are treated as categorical data to eliminate over-plotting. Furthermore, to maintain high readability in a small area, the data features are represented by the ratio of colors.

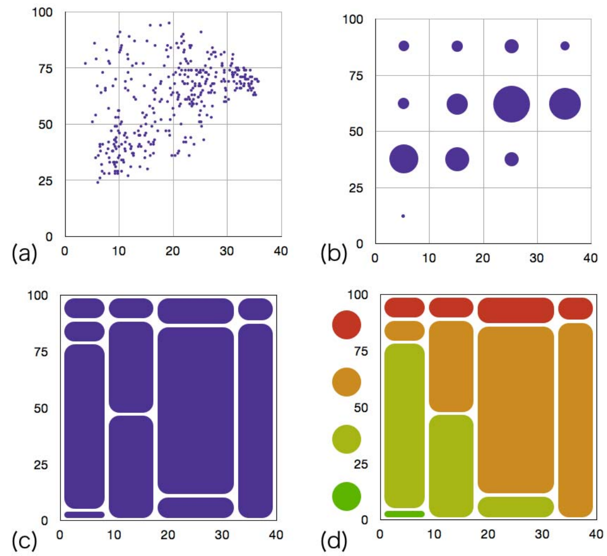


Figure 1. Generation process of Colored Mosaic Plot

B. Colored Mosaic Matrix

We developed Colored Mosaic Matrix, which is an extension of Mosaic Matrix using a color representation. Colored Mosaic Matrix is a technique that allows the distribution and features of data to be read from the proportion of color or a color pattern.

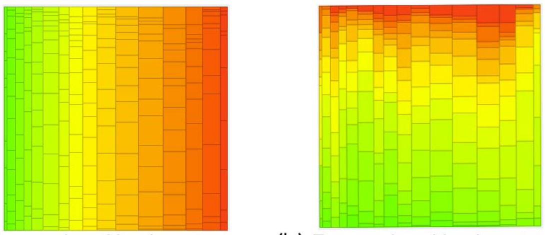
To reduce over-plotting, quantitative data are first converted into categorical data. Figure 1(a) and 1(b) show a schematic data representation before and after the conversion, respectively. In each dimension of quantitative data, the value range is subdivided into small ranges, and each range is treated as a category. In a category, the frequency and order exist. This makes it possible to represent data using fewer markers. As shown in Figure 1(c), two-dimensional categorical data are visualized by Mosaic Plot.

We developed Colored Mosaic Plot, which is composed of colored rectangles (see Figure 1(d)). In Colored Mosaic Plot, the identification of each rectangle is possible. Placing a Colored Mosaic Plot into a matrix form, called a Colored Mosaic Matrix, the visualization of high-dimensional data is made possible.

C. Representation of Features by Coloring

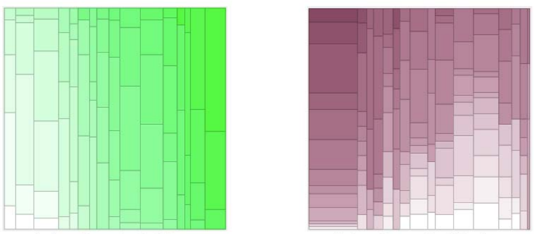
The coloring rule has a great influence on reading the data features. We focus on a distribution of the categories and on the correlation, as criteria to determine the data features. We therefore developed coloring techniques based on these criteria.

Coloring technique focusing on categories. The purpose of this technique is to represent the distribution of categories. In the prototype, we made it difficult to distinguish the colors when a wide variety of colors occurs. Therefore,



(a) Focused on X-axis category (b) Focused on Y-axis category

Figure 2. Coloring examples focused on categories



(a) C= 0.969 (b) C= -0.514

Figure 3. Coloring examples focused on the correlation

we designed this coloring technique by focusing on either dimension of Mosaic Plot to improve the readability. We adopted a gradient hue between green and red in ascending order of the categories.

Figure 2 shows Mosaic Plots to be colored differently. If coloring is performed on the X-axis (see Figure 2(a)), since the width of the X-axis of each category is unified, a striped pattern appears. By looking at the widths of the stripes, it is possible to read the distribution of categories for the X-axis dimension. For example, in Figure 2(a), many hues from yellow to red can be seen. This means that many high values exist. On the other hand, the coloring in the Y-axis shows the distribution of Y-axis categories based on the distribution of colors (see Figure 2(b)). Here, the height of each rectangle depends on the category of both the X and Y dimensions. This allows the reading a two-dimensional relationship by using color.

Coloring technique focusing on the correlation between dimensions. This coloring technique is intended to enable guessing the approximate shape of the data. This is designed particularly for pairs of originally quantitative data dimensions. In this coloring, the hue is based on the correlation coefficient in two dimensions. Therefore, all rectangles in a mosaic plot are filled with the same color.

Figure 3 shows a coloring example based on the correlation. According to the hue, the correlation can be judged as either positive or negative. The brightness and saturation represent the intensity of the correlation and the distinction of the Y-axis categories.

D. Category Partitioning Algorithm for Quantitative Data.

In the dimension of quantitative data, the range of categories is determined using a partitioning algorithm. The partitioning algorithm affects the shape, size, and color of each rectangle in Colored Mosaic Plot. Therefore, we developed several algorithms that can be used according to the data distribution or based on the purpose of the analysis.

Partitioning with respect to the maximum and minimum values. The value range is subdivided into equal intervals based on the maximum and minimum values in each dimension. Each range is regarded as a category in the dimension. This algorithm has an advantage of being intuitive and allowing an easy understanding of the data distribution. However, when an outlier exists, the range of each category will increase. As a result, most of the values are concentrated in certain categories, which is difficult to analyze in detail.

Partitioning based on the distribution of data. This algorithm determines regions to be divided according to the data amount. First, the dividing range that contains the predetermined amount of data around the average value is determined, and this range is then split. If p is the number of divisions, the dividing region is subdivided into $p-2$ categories. In addition, each region outside is treated as a category. This algorithm has the advantage in that the values are not too concentrated in certain categories, and there is little influence from the presence of outliers. This is useful when we analyze a concentrated data area in detail.

IV. Development

We developed a tool to analyze high-dimensional data from an overview, which enables us to drill down to a detailed level. The tool provides Matrix View and Detail View. Matrix View allows an overview of all data to be obtained, whereas Detail View allows the features to be obtained in detail.

A. Representation Technique Used in the Tool

Matrix View shows all possible combinations of dimensional pairs in high-dimensional data using Colored Mosaic Matrix. This allows the features of each dimension pair of high-dimensional data to be expressed.

Colored Mosaic Plot is placed in the center of Detail View, which displays one pair of dimensions in detail. The names of the X-axis categories are placed at the bottom, and those of the Y-axis categories on the left. To facilitate the reading of the data distribution, Detail View also displays an area graph to express the distribution. An area graph represents the frequency of each value in each quantitative data dimension.

B. Interface of the Tool

Figure 4 shows a screen shot of the tool we developed. Matrix View appears on the left side of the screen, and

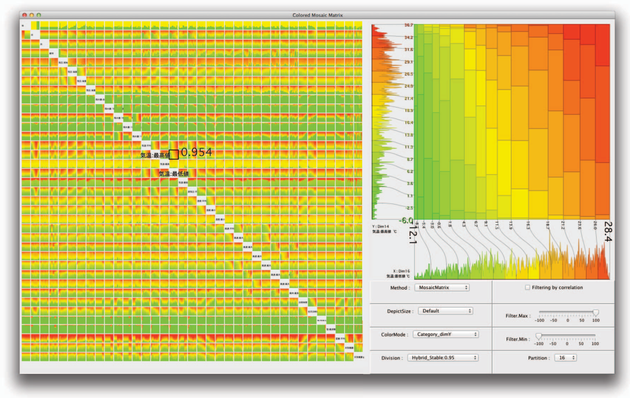


Figure 4. Screenshot of the proposed analytical tool

a detailed view is in the upper-right zone. In addition, there is an operation panel at the lower-right part of the screen for regulating variables that have an influence on the visualization.

In Matrix View, the dimension names for each axis of Colored Mosaic Plot under the mouse pointer are enlarged. If both dimensions of Colored Mosaic Plot consist of quantitative data, their correlation coefficient is displayed near the mouse pointer. Matrix and Detail views are associated, and thus Colored Mosaic Plot to be displayed in Detail View can also be selected arbitrarily in Matrix View.

In Detail View, the number of records corresponding to the rectangle under the mouse pointer is displayed. By clicking on a rectangle, we can select a group of records contained in the rectangle. When the records are selected, each rectangle is divided into two, depending on the ratio of records selected. In this way, it is possible to read the proportion and distribution of the records selected against all existing records.

We can configure this tool such that it redisplays the visualization with only the selected records so as to filter the data under only certain conditions. This feature enables a more detailed data analysis.

V. Evaluation Experiment

A. Overview of the Experiment

This experiment was conducted as an evaluation of the usefulness of Colored Mosaic Plot. In terms of accuracy, we evaluated the usefulness of the reading comprehension and ease of understanding of each expression. Based on the evaluation of Colored Mosaic Plot, we next discuss the proposed Colored Mosaic Matrix further.

The target users of our tool are experts who analyze data through visualization. In this experiment, we therefore selected seven subjects specialized in information visualization. We confirmed before the experiment that they belong to the majority of the population in terms of their color vision.

The task in this experiment is focused on determining what is required to read the distribution of quantitative data when analyzing high-dimensional data. The task was performed using an experimental tool combining Scatterplot and Colored Mosaic Plot. Based on the rate of correct answers during the task, we assessed the readability of our representation under each condition.

The experimental procedure is as follows. 1) Receive a description of the representation used in the experimental tool. 2) Solve several practical tasks until the subjects become accustomed to the tool. 3) Solve all tasks. 4) Respond to a questionnaire regarding the representation.

B. Experimental Task

For the data used in this experiment, 16-dimensional data (containing 30,000 records) were created. The data are composed of only quantitative dimensions, whose distribution is either skewed or uniform. The configuration of the records is such that the correlation coefficients are uniformly distributed.

The subjects were asked to solve the task using our developed experimental tool. Colored Mosaic Plot or Scatterplot was shown as a question on the left of the screen, and five Scatterplots as choices were provided on the right. Each subject chose the same data distribution shown in the question. The subjects could switch the coloring techniques used in Colored Mosaic Plot. This is because switching techniques are used for further analysis in real-world cases.

The condition parameters of the task are set as follows.

- There are five combinations of conditions regarding the drawing area and the existence of an area graph.

$$\begin{cases} \text{700 pixel} & \begin{cases} \text{with Area Graph} \\ \text{without Area Graph} \end{cases} \\ \text{24 pixel} & \text{without Area Graph} \\ \text{12 pixel} & \text{without Area Graph} \\ \text{6 pixel} & \text{without Area Graph} \end{cases} \tag{1}$$

- There are four combinations of conditions regarding the visualization method and the division number of categories (let $P(n)$).

$$\begin{cases} \text{Colored Mosaic Plot} & \begin{cases} P(16) \\ P(8) \\ P(4) \end{cases} \\ \text{Scatterplot} & \end{cases} \tag{2}$$

The combination of the above resulted in 20 conditional parameters. In this experiment, we had each subject carry out each task six times with 20 conditional parameters, i.e., 120 times in total.

C. Result

Figure 5 shows the results of the average rate of correct answers by each task condition parameter. The horizontal axis expresses the drawing area and the existence of an area graph. The color of the bar graph represents in the cases of Colored Mosaic Plot in each $P(n)$ and Scatterplot.

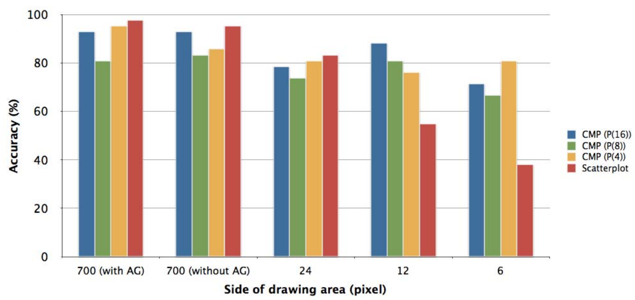


Figure 5. The average rate of correct answers by each task parameter

D. Considerations

Several considerations regarding the experimental results are described below. For a comparison of the average rate of correct answers, a dependent two-tailed t-test for the paired samples was used at a 5% significance level.

Relationship between the division number of categories and the drawing area size. In each drawing area of Colored Mosaic Plot, the rate of correct answers was assayed for the presence of significant differences due to differences in the division number of categories. The results of the t-test showed no significant differences in the drawing area of more than 24 square pixels. On the other hand, in a drawing area of 12 square pixels, there was a significant difference between the rate in $P(16)$ and $P(4)$. In addition, in the case of 6 square pixels, a significant difference was confirmed between $P(8)$ and $P(4)$.

Influence of Area Graph. Based on the feedback obtained from the questionnaire and the correct rate in the presence or absence of an area graph (AG), we considered to what extent an AG is effective for reading the data distribution. Through the t-test, we were unable to confirm a significant difference between the correct rate of tasks with/without an AG. Through the questionnaire, we obtained opinions such as "I had a higher confidence in my answer with an AG," and "an AG is the most easy-to-understand representation." From these, we regard an AG as easy to understand and effective for facilitating data reading.

Comparison between Colored Mosaic Plot and Scatterplot. We performed a t-test on the average rate of correct answers from each visualization method. We adopted the division number of categories resulting in the largest correct rate for each size of the drawing area. We assumed n to be the pixel size of one side of the drawing area, $\mu_C(n)$ to be the average rate of correct answers using Colored Mosaic Plot, and $\mu_S(n)$ to be the average rate of correct answers using Scatterplot. Table I shows the average rate for each size for each method, and the p-values of the t-test. As the results of the t-test show, there was no significant difference between $n = 700$ and $n = 24$. On the other hand, there was a significant difference between $n = 12$ and $n = 6$. Judging from Table I, we assumed $\mu_C(n) > \mu_S(n)$.

Table I
THE AVERAGE RATE OF CORRECT ANSWERS FOR EACH VISUALIZATION METHOD AND THE RESULTS OF THE T-TEST

n	700	24	12	6
$\mu_C(n)$	92.86%	80.95%	88.10%	80.95%
$\mu_S(n)$	95.24%	83.33%	54.76%	38.10%
p-value	0.6036	0.8588	0.0177	0.0057

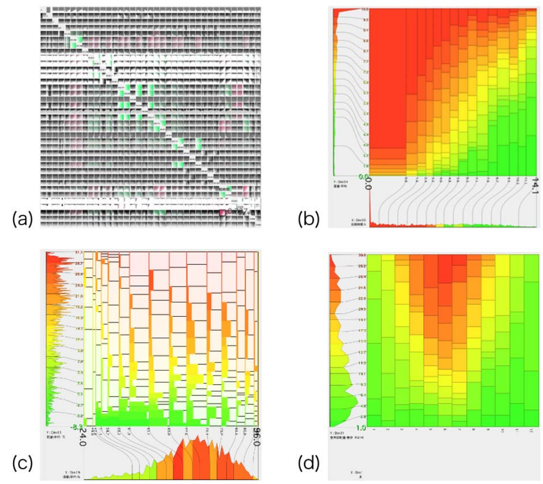


Figure 6. Visualization examples of weather data

There was no significant difference between the correct answer rate by Colored Mosaic Plot and Scatterplot in a sufficiently large area. On the other hand, the higher rate of correct answers was confirmed by Colored Mosaic Plot in an area of 12 square pixels or smaller. Colored Mosaic Plot could maintain readability in the entire drawing area. This indicates that Colored Mosaic Matrix is useful as a method for obtaining an overview of high-dimensional data.

VI. Use Case

A. Target Data

For data visualization using our tool, we obtained meteorological data from five observing stations in Japan from the Japan Meteorological Agency Website[1]. 37-dimensional data were used, and the acquisition period was from September 1, 2011, to August 31, 2012.

B. Data Analysis Using the Developed Tool

Figure 4 shows the visualization results for meteorological data. Matrix View in Figure 4 shows that the hue is within the pattern of horizontal stripes. This is because it uses a coloring algorithm focused on the distribution of Y-axis dimensions. For example, the dimensions in the green row

[1] http://www.data.jma.go.jp/obd/stats/etrn/index.php

represent the dimensions of precipitation and snowfall by the day. This results from a few days of rain or snow throughout the year. In one row, many red through yellow hues could be observed (the dimension is the cloud cover average). This indicates that there were many cloudy days.

Figure 6(a) shows the visualization results using the coloring algorithm based on the correlation of dimensions. To reduce the influence of outliers in each dimension, it uses the partitioning algorithm of the category based on the data distribution. In Figure 6(a), Colored Mosaic Plot is represented by a bright red color on the bottom right. This red color represents a strong negative correlation between the dimensions in the Colored Mosaic Plot. We confirmed that the dimension of the X-axis is the duration of sunshine, and the Y-axis is the average duration of cloud cover. Figure 6(b) shows the same Colored Mosaic Plot in Detail View using the coloring algorithm focusing on the distribution of Y-axis dimensions. From the distribution of colors, it can be seen that a day with a higher average value of cloud cover has fewer hours of sunshine.

From Detail View, out of the five stations, we selected only the data in Sapporo, which is located in the most northern part of the five stations. Figure 6(c) shows an example of Detail View under the conditions of the data selected. The X-axis shows the average humidity, and the Y-axis shows the average temperature. From Figure 6(c), it can be seen that the temperature and humidity in Sapporo are relatively lower than at the other stations. Here, we redrew the plot using the records for only Sapporo. Figure 6(d) shows Detail View representing the relationship between the month and the amount of sunlight in Sapporo. This indicates a reduction of the amount of sunlight in the winter period from November to February.

VII. Conclusion

In this paper, we developed Colored Mosaic Matrix as a visualization method for the purpose of obtaining an overview of high-dimensional data in a limited drawing area. Using colors to represent the distribution of data, Colored Mosaic Matrix enables us to read the data features even in a small drawing area. To deal with quantitative data as categorical data, we also proposed some algorithms for splitting multiple categories. To represent the data based on the category, our method can visualize even high-dimensional data with a large number of records.

Using an experimental task of reading a data distribution using Colored Mosaic Plot, we investigated the readability of the proposed representation. It was confirmed quantitatively based on the rate of correct answers that Colored Mosaic Plot maintains a high readability regardless of the size of the drawing area. This indicates the usefulness of Colored Mosaic Matrix in high-dimensional data analysis.

Through this study, we were able to obtain knowledge from an overview of high-dimensional data, and based on this, performed a detailed analysis. In the future, this can represent a useful tool in the development of analytical methods and high-dimensional data analysis.

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