Hierarchical data visualization of Gender Difference: Application to Feeling of Temperature

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***Abstract*—New social problems caused by data bias have been an important issue in recent years. Data bias is sometimes difficult to determine using only quantitative methods, and it requires human decision-making to resolve. Visualization technology can help humans understand data bias and assist with this issue. This paper proposes a visualization method for detecting intersectional bias caused by multiple attributes. The method generates a hierarchical structure by classifying data items according to multiple attributes, and applies a hierarchical data visualization method equipped with band charts. It provides a visualization that gives an overview of the entire data and makes it easy to detect biases in a particular subset of the data. This paper introduces an application to the gender difference in the feeling of temperature with air conditioning systems, and presents the results of participant evaluations to verify the effectiveness of the proposed visualization over baseline implementation.**

***Index Terms*—Hierarchical data visualization, Gender difference, Feeling of temperature**

I. Introduction

Data bias has caused new social problems with the spread of machine learning and data science. For example, biases in training data may cause biases in the results of machine learning. Examples of such social problems include the disadvantageous results for women when machine learning is introduced into the hiring process of a company, and the difference in the percentage of men and women who are approved for credit cards and mortgage loans.

Eliminating disadvantages caused by specific attributes is very essential to establish a highly equitable society. In particular, the benefit imbalance caused by gender has been of great importance in recent years. A new keyword, Gendered Innovation, is attracting attention as an effort to solve this problem.

Data bias is not always found in the entire dataset. Rather, bias is often found in a subset of the data that has certain personal attributes. Therefore, it is important to observe the differences in the numerical distributions of each personal attribute in the dataset while finding the data bias. The personal attributes here include, for example, gender, region, race, and generation. In other words, bias is often found in a subset of the dataset that is composed of individuals who have specific personal attributes and satisfy other factors. For example, specifically, it can happen that "Women whose occupation is zero have a higher percentage of disapproval of mortgage loans". This bias caused by multiple attributes and factors is called intersectional bias.

Such biases include qualitative and subjective issues, and therefore, a quantitative determination is not always a sufficient solution. In addition, human decision-making is necessary to find solutions to biases. In other words, it is useful that the analysts of the data bias understand the data and discover biases in the data by humans, rather than applying fully automatic techniques to find the biases hidden in the data. Visualization techniques have been actively studied as a technique to help us understand the data, and are useful for the purpose of discovering biases in data. In particular, to discover biases in specific parts of datasets, visualization techniques that allow both an overview of the entire dataset and the discovery of a specific subset of the dataset is useful. From this perspective, we aimed to develop a visualization method that satisfies the following requirements. From this perspective, we aimed to develop a visualization method that meets the following requirements.

1: Enable to overview of the entire dataset.
2: Assist the discovery of bias in a subset divided based on personal attributes.
3: Archive a visual representation that makes bias easy to detect.

This paper proposes a method to visualize the bias of numerical distribution in a dataset consisting of a large number of persons. This study assumes that a person is a data element and each person has various attribute values. The proposed method divides these data elements hierarchically by attributes and visualizes them using our hierarchical data visualization method [7]. Here, it fills a rectangular region representing a hierarchy with multiple band charts. By representing the numerical distribution of a certain attribute value in its band charts, it visualizes differences in numerical distribution due to specific attributes. For example, to visualize the bias between men and women, two rows of band charts for men and women are filled in. The hierarchical data visualization applied in this study satisfies Requirement 1 because it aims to provide an overview of the entire hierarchical dataset, and Requirement 2 because it classifies and displays data hierarchically based on the attributes of the data elements. It also satisfies Requirement 3 because it makes it easy to find bias among attributes by

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using a visual representation of a series of band charts.

This paper introduces an application of the presented visualization method to the gender difference in the feeling of temperature with air conditioning systems, and discusses the effectiveness of this method.

II. Related work

A. Visualization of data bias

Visualization of data bias is a well-focused issue over the last several years. One of the motivations of this study is that the fairness of machine learning has been focused on as a major social issue and data bias is its big factor. In addition, it is useful to solve this problem through active human intervention in the machine learning process. The following are examples of recent studies on the visualization of data bias.

Cabrera et al. [5] presented FairVis, a visual analytics system to prevent discrimination and unequal learning outcomes by grouping compositely sensitive attributes such as race and gender and focusing on the intersectional bias that occurs between groups. Ahn et al. [2] presented FairSight that visualizes the three phases, data processing (Data), selection of learning models (Model), and generation of rankings as learning outcomes (Outcome), to achieve the visualization focusing on fairness. Wang et al. [12] presented DiscriLens which supports comprehensive visual analytics of bias in machine learning by combining a discrimination detection module with a visualization module. Tochigi et al. [11] visualized the bias of machine learning in the recommendation system by displaying the difference between the viewing history and the recommendation results in the machine learning movie recommendation system data.

The visual representation in these systems consists of multiple views such as simple bar charts, line charts, and scatterplots. Thus, users need to search for biases in the data through repetitive operations through multiple views. On the other hand, most information visualization systems are designed according to the operation scenario proposed by Schneiderman [10], “Overview first, zoom and filter, then details on demand”. The first overview is an important component guiding the next appropriate operations. Based on this idea, this study differs significantly from the previous studies mentioned above in that we focus on letting users find the bias in a particular part of the first overview.

B. Intersectional bias

Bias is not always present in the entire dataset. Rather, bias is often found in a subset of the data. In particular, the bias found in a subset that satisfies multiple specific attributes is called an intersectional bias. Intersectional bias is easy to overlook and not easy to mitigate. As an example of a countermeasure to this problem, Kobayashi et al. [9] proposed a method called One-vs-One Mitigation. This method attempts to improve the fairness of binary classification by machine learning applied comparison processing between subset pairs.

C. Hierarchical data visualization

Itoh et al. [6], [7] proposed a hierarchical data visualization method. It represents the leaf nodes of hierarchical data as rectangular icons, branch nodes as rectangular frames, and the hierarchical structure as a nested structure of two-dimensional rectangular groups. Then, by arranging these in the smallest possible screen space, it displays the entire hierarchical data on a single screen. Figure 1 shows an example of visualization using this method.

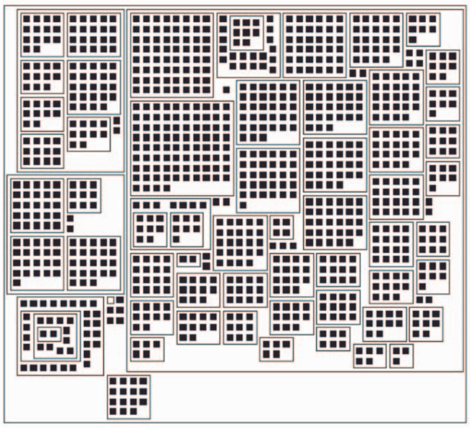

Fig. 1. An example of visualization using a hierarchical data visualization method proposed by Itoh et al [7].

This visualization method fills the screen with rectangular areas and icons. This type of visualization method that fills the screen with visual elements such as rectangles and icons is called “space-filling”. Treemaps [4], [8] are representative examples of space-filling hierarchical data visualization methods. Experimental results [7] show that it is superior to Treemaps in terms of the shape of the rectangular regions generated by the algorithm presented by Itoh et al. In this respect, it is more suitable for the purpose of this study than Treemaps.

Voronoi Treemap [3] is an example of a type of visualization method that fills the screen with non-rectangular shape regions. On the other hand, this method needs to fill the screen with rectangular regions because it represents the data bias in a band chart, as described below. In this sense, this method uses the method proposed by Itoh et al.

III. Visualization of bias as hierarchical data

A. Supposed input dataset

The proposed method assumes that the following dataset is given. Here, A represents the entire dataset consisting of a set of persons, a_i represents the i-th person, and n represents the number of persons in the dataset.

$$A = \{a_1, a_2, \ldots, a_n\}$$

Here, a_i corresponding to the i-th person has the following variables. e_i is the real value to be visualized, g_i is the gender of the i-th person, r_{ij} is the attribute value of the j-th real type variable, and c_{ik} is the attribute value of the k-th categorical type variable.

$$a_i = \{e_i, g_i, r_ij, \ldots, c_{ik}, \ldots\}$$

B. Generation of hierarchical structures and display of band charts

The proposed method hierarchically classifies a group of persons using multiple attribute values selected by the user among the attribute values r_{ij} or c_{ik}, and forms a tree structure. If the dataset contains the intersectional bias of real value e_i caused by the multiple attribute values selected by the user, it is visualized under a particular node in this tree structure. The proposed method visualizes this tree structure with the aforementioned hierarchical data visualization method [7]. Figure 2 shows an example of visualization. The proposed method generates a tree structure by iterating the process of selecting one attribute at a time and classifying the person based on that attribute. In the visualization of the tree structure, the outer rectangular region corresponds to the classification result with the first selected attribute, and the inner rectangular region corresponds to the classification result with the later selected attribute.

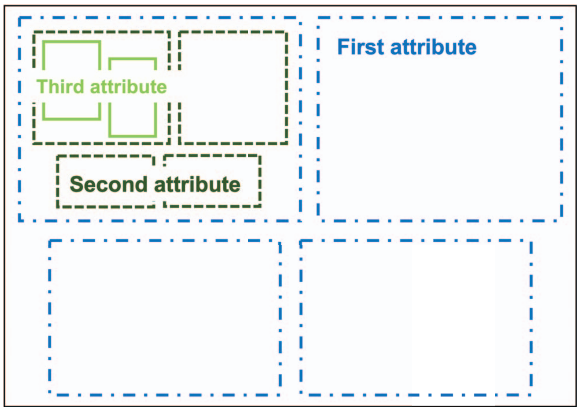

Fig. 2. Tree-structured representation of person group dataset based on multiple attributes.

The visualization method originally represents the leaf nodes by square icons, whereas the method represents the distribution of e_i of a group of persons corresponding to a group of leaf nodes by multiple band charts. Specifically, the proposed method classifies a group of persons according to certain attributes, divides the real number e_i into several classes for each attribute, and tabulates the number of persons in each class. Then, it displays the results for each class for each attribute in band charts. In our current implementation, the number of classes is fixed at 7.

Figure 3 shows an example of a band chart, using the visualization of bias between men and women as an example. The left side shows the numerical distribution of e_i for men while the right side shows the numerical distribution of e_i for women in this example. The proposed method uses the HSI color system to calculate the color of each region of the band chart, and calculates the color of each class of the numerical distribution according to the following principles.

- Hue: Assign a value to each attribute. In the example in Figure 3, the hue of men is blue while the hue of women is red.
- Saturation: Assign the lower value if a value is closer to the median of each class to the overall mean. Or, assign the higher value if a value is closer to the median of each class to the maximum/minimum value.
- Intensity: Assign the higher value, the higher the median value for each class.

In the example shown in Figure 3, the band chart shows that the total number of men is larger than that of women, that the proportion of men who feel hot is higher, and that the proportion of women who feel cold is higher.

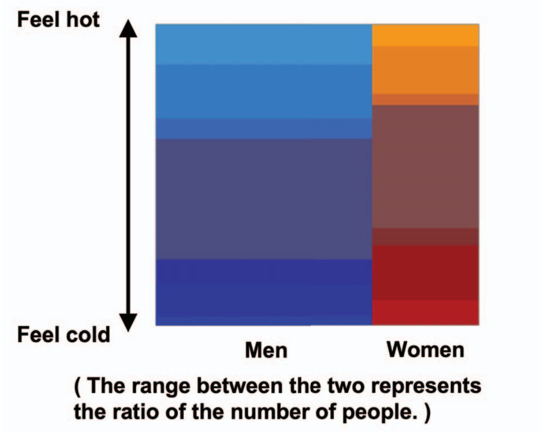

Fig. 3. Representation of bias among attributes by multiple band charts.

C. Interaction

Our implementation features radio buttons for selecting multiple (three in the current implementation) attributes before generating the hierarchical structure. The hierarchical structure is regenerated and the display is updated each time the three attributes are selected and the "refresh" button is pressed. Moreover, hovering the cursor over the band chart display the corresponding three attributes in the text.

IV. Application Examples on the Feeling of Temperature with Air Conditioning System Data

This paper presents an application example of the open dataset [1] of the feeling of temperature with air conditioning systems. We extracted the following attribute values for 32,373 subjects from this dataset.

- TS: Evaluation value for temperature. 0 is just right, "1, 2, 3" are hot, "-1, -2, -3" are cold.

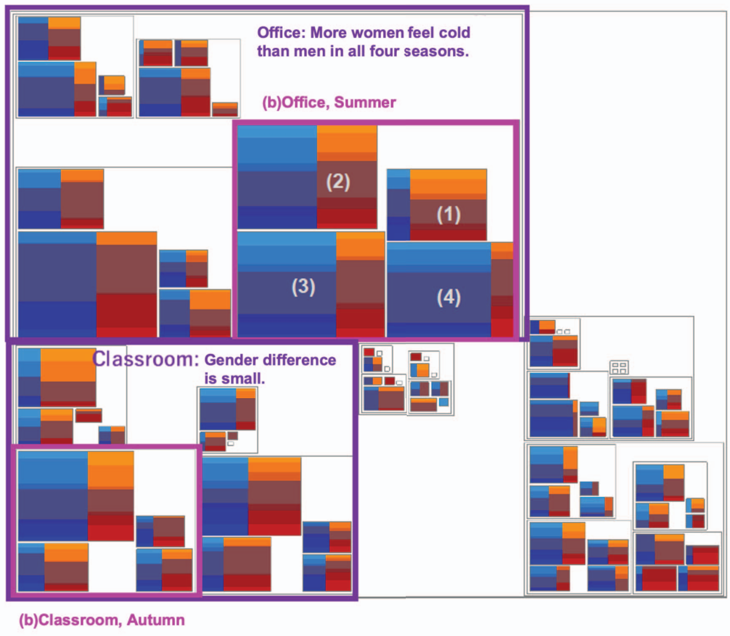

Fig. 4. Visualization example (1). The persons were classified in order of Building, Season, and Cloth.

- Sex: Gender in the biological sense. Persons who answered other than “man” or “woman” were excluded from this example.
- Age: Age.
- Cloth: Real value for the thickness of the clothing. The larger the value, the thicker.
- Metab: Real value for metabolic rate.
- Season: Four category values: spring, summer, fall, and winter.
- Building: Five category values: office, classroom, residential, senior citizen facility, and others.
- Strategy: Three category values for air conditioning, ventilation, and mixing.

In summary, TS corresponds to e_i, Sex to g_i, Age, Cloth, Metab to r_{ij}, and Season, Building, Strategy to c_{ij}.

A. Visualization example (1)

Figure 4 shows the visualization result applying the person classification with the attribute values of Building, Season, and Cloth, in that order. Outer rectangular frames in the visualization result correspond to the five category values of Building, and inner them are rectangular frames corresponding to the four category values of Spring, Summer, Fall, and Winter. Further inside are rectangular regions corresponding to the four intervals of Metab. The band charts inside the office frame at the top of the visualization result show that dark red occupies a larger area than dark blue. This indicates that more women than men judged it to be “cold”. The inner frame (a) corresponds to summer, and the four regions inside it indicate that (1) is the lightest and (4) the thickest clothing. The thickness of the band charts indicates that women are more likely to wear light clothing in summer, while men are more likely to wear thick clothing. Moreover, the color ratio shows that men judged it to be “hot” because of the large light blue area, while women judged it to be “cold” because of the large dark red area, especially in (3) and (4). This indicates that men and women tend to differ in their judgments. On the other hand, in the band chart inside the classroom frame in the lower left of the visualization results, there is no significant difference in the area of light blue and orange, and dark blue and dark red. So this indicates that the judgements between men and women in terms of the feeling of temperature in the classroom are not much different. However, in the fall corresponding to the inner flame (b), we found a complex discrepancy in the judgment of the feeling of temperature between men and women, depending on the thickness of their clothing.

B. Visualization example (2)

Figure 5 shows the visualization results applying the person classification by using the attribute values of Strategy, Season, Building, in that order. The light blue and orange areas in (a) corresponding to summer are larger than the dark blue and dark red areas inside the ventilation flame at the upper left of the visualization screen. This indicates that many people of both men and women judged it to be “hot”. Conversely, the dark blue and dark red areas are larger than the light blue and orange areas in (b), which corresponds to winter. This indicates that many people of both men and women judged it to be “cold”. The inner area of the air conditioner frame in

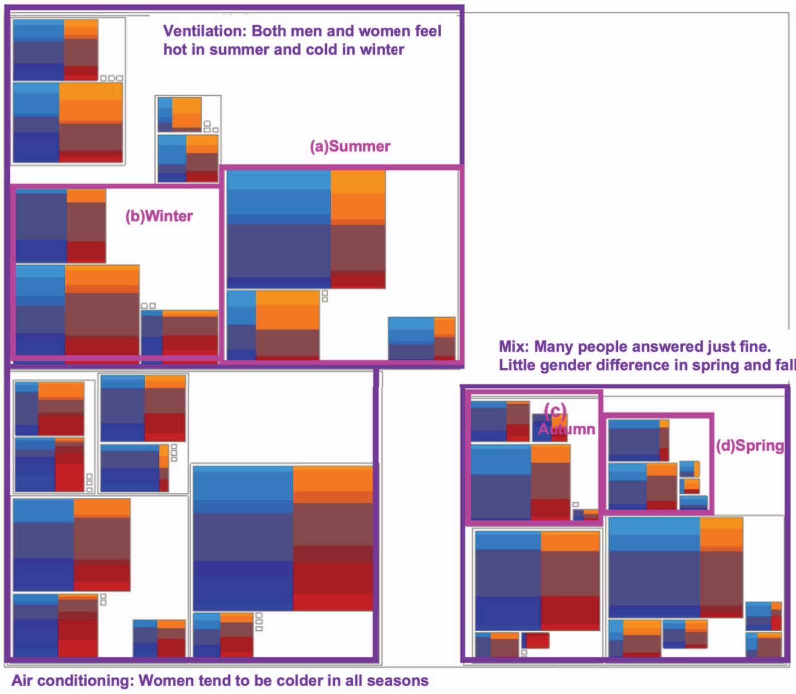

Fig. 5. Visualization example (2). The persons were classified in order of Strategy, Season, and Building.

the lower left of the visualization screen shows that the dark red area is larger than the dark blue area in almost all band charts, indicating that women are more likely to judge it as "cold" regardless of the season or location. Inside the mix at the lower right of the visualization screen, the dark red area is larger than the dark blue area in (c), which corresponds to autumn, and in (d), which corresponds to spring, indicating that women are more likely to judge it to be "cold". On the other hand, the difference in judgment between men and women is smaller in summer and winter, suggesting that a mixture of air conditioning and ventilation is desirable in summer and winter.

V. Evaluation by participant experiment

We conducted a participant experiment to verify the effectiveness of the proposed method. The subjects were 12 students majoring in computer science. This experiment prepared, in addition to the visualization results by the proposed method (hereinafter referred to as "P"), the visualization results by the following two baseline implementations (hereinafter referred to as "B1" and "B2").

- B1: Visualization results simply applying the method proposed by Itoh et al [7]. Band charts are not displayed; the icons corresponding to each of the people in the dataset are displayed.
- B2: Visualization results that display only a set of band charts, without any rectangular flames representing the hierarchical structure.

We used the dataset of the temperature feeling with air conditioning presented in the previous section to generate visualization examples.

The participants were presented with the three visualization results (P, B1, and B2) in a random order, and were asked to answer the following questions Q1-Q8 on a 7-point Likert scale (1: not at all agree to 7: strongly agree) for each visualization result. Q1 and Q2 are questions to verify Requirement 3, Q3 and Q4 are questions to verify Requirement 2, and Q5 is a question to verify Requirement 1. Q6-Q8 are questions taken from the NASA Task Load Index (NASA-TLX). Q6 to Q8 are marked with a superscript "-" because a higher response value indicates a negative result.

- Q1: Easy to find which combination of the three attributes is "more male" or "more female".
- Q2: Easy to find which combination of the three attributes is "more men feeling hot/cold" or "more women feeling hot/cold".
- Q3: Easier to understand which single of the three attributes is responsible for the difference in responses between men and women.
- Q4: Easier to understand which "combination of multiple attributes" among the three attributes is responsible for the difference in responses between men and women.
- Q5: Satisfactory as a visualization for overview and analysis of gender differences in the temperature feeling.

Q6$^-$: Perceptual activities such as contemplation and memory are necessary when using this visualization.

Q7$^-$: Great effort is needed to understand this visualization.

Q8$^-$: Feel frustrated while looking at this visualization.

TABLE I

RESULTS OF PARTICIPANT EXPERIMENTS FOR COMPARISON WITH BASELINE.

	P	B1	B2
Q1	6.33	3.25*	5.42*
Q2	5.17	2.33*	4.50*
Q3	4.92	2.25*	3.33*
Q4	4.42	2.00*	3.33*
Q5	5.67	2.50*	3.92*
Q6$^-$	4.33	4.83	4.42
Q7$^-$	3.92	5.33	4.83
Q8$^-$	2.92	5.50*	4.00

Table V shows the averages of the responses as an interval scale. Wilcoxon's rank-sum test was applied to "P and B1" and "P and B2", and results with $p < 0.05$ were marked with "*".

The results from Q1 to Q5 all show that the proposed method (P) is significantly higher than the baseline (B1, B2). This suggests that the combination of "representation of hierarchical structure" and "band chart" is effective in satisfying requirements 1, 2, and 3.

On the other hand, the results of Q6 to Q8 were all rated higher than the baseline for the proposed method, but the results are not statistically significant. Since this study mainly targets users who are engaged in data analysis in their daily work, in this sense, we do not consider that "perceptual activity is necessary" or "effort is required" to be a major issue. On the other hand, if we suppose this visualization is ever used for presenting widely to the general public, such as consumers, the need for perceptual activity and effort may hinder their dissemination. In other words, more ingenuity in visualization design is necessary when expanding the target users to include general consumers.

VI. CONCLUSION

This paper proposed a method to visualize intersectional bias in a dataset of a large number of persons as hierarchical data. This method classifies groups of persons composing the dataset hierarchically based on user-selected attributes, and visualizes them using our own hierarchical data visualization method. This method represents the bias of the numerical value distribution using multiple band charts to represent the numerical values that a group of persons corresponding to a specific node in the hierarchical structure. This paper presented the visualization results using the dataset of the temperature feeling with air conditioning and the results of participant experiments.

One of the future issues is to deal with the dataset with a very large number of attributes. The proposed method requires an attribute selection operation to generate a hierarchical structure. This operation becomes very complicated for the dataset with a very large number of attributes. Therefore, we would like to develop a method to automatically select combinations of attributes that are worth visualizing.

Next, we would like to have case studies for various datasets other than the temperature feeling with air conditioning. Also, we would like to visualize biases in numerical distributions caused by attributes other than gender (e.g., generation, region, race, occupation). Furthermore, we would like to utilize the proposed method as a tool for correcting biases in machine learning training datasets, and verify its effectiveness in the field of machine learning.

The participant experiments presented in this paper used still images of the visualization results and do not show the actual operation of the visualization system. Therefore, we would like to conduct task-based participant experiments while actually operating the visualization system to measure the level of achievements of the tasks.

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