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Grouping Effect for Bar Graph Summarization for People with Visual Impairments

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Abstract

When communicating numerical data to people with visual impairments (PVI), summaries provided by current data visualization solutions tend to lose important information during summarization. To address this issue, our work focuses on summarization through bar grouping in bar graphs. Neither the effect of grouping nor the appropriate granularity of grouping has been discussed so far. Therefore, we investigate the cognitive effects of grouping and its relationship to the number of groups. A user study involving nine PVI (five blind and four with low vision) revealed that summarization through bar grouping conveys information significantly more accurately compared to simply reading individual data points, despite the inherent error produced by grouping. Additionally, we propose a cognitive error model to explain the characteristics of the observed errors.

CCS Concepts

• **Human-centered computing → Accessibility systems and tools**.

Keywords

Bar graph, summarization, people with visual impairments, cognitive load

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1 Introduction

Data visualization, including graphs, tables, and diagrams, is widely used to effectively convey key points of numerical data, allowing readers to understand and explore the information more easily. Graphs, in particular, are frequently used and can be found in various media, including news articles, financial reports, scientific papers, and web content. Sighted individuals can efficiently grasp the key points of numerical data from the shape of a graph and access key information, such as outliers, trends, notable high data points, and distribution patterns, without reading individual data points.

However, people with visual impairments (PVI) are often excluded from the benefits of data visualization, making it difficult for them to access and understand numerical data. Conventional approaches, including the development of deep learning models for generating summaries [2, 5, 27, 29, 33, 42, 45] and data visualization [3, 9, 16, 19–22, 26, 32, 36, 38–40], typically provide alternative text that describes data content using statistical values such as maximum, minimum, and average. However, they are less informative in conveying the key points with numerical data. In contrast, simply reading individual data points ensures that every detail of the data is conveyed, but understanding the information requires a massive mental effort, referred to as a high cognitive load. Consequently, PVI face difficulties in effectively accessing numerical data. One might assume that using large language models (LLMs) is sufficient for generating informative sentences in the desired form. However, there is no scientific verification of what type of summary would be most appropriate and its underlying reasons.

This paper explores the grouping of bars with similar values to emulate the visual effect perceived by sighted individuals. To explain this, let us consider an example shown in Fig. 1(a), assuming bars in a graph are arranged in descending order. As shown in Fig. 1(b), grouping bars with similar values helps to summarize the numerical data. Fig. 1(c) shows the generated summary, which helps to easily understand the overall information of the numerical data. Many people would agree that the cognitive load decreases as the number of bars decreases in a graph. Hence, the summarization into a smaller number of groups is easier to understand, but inherently less accurate and conveys erroneous information. Conversely,

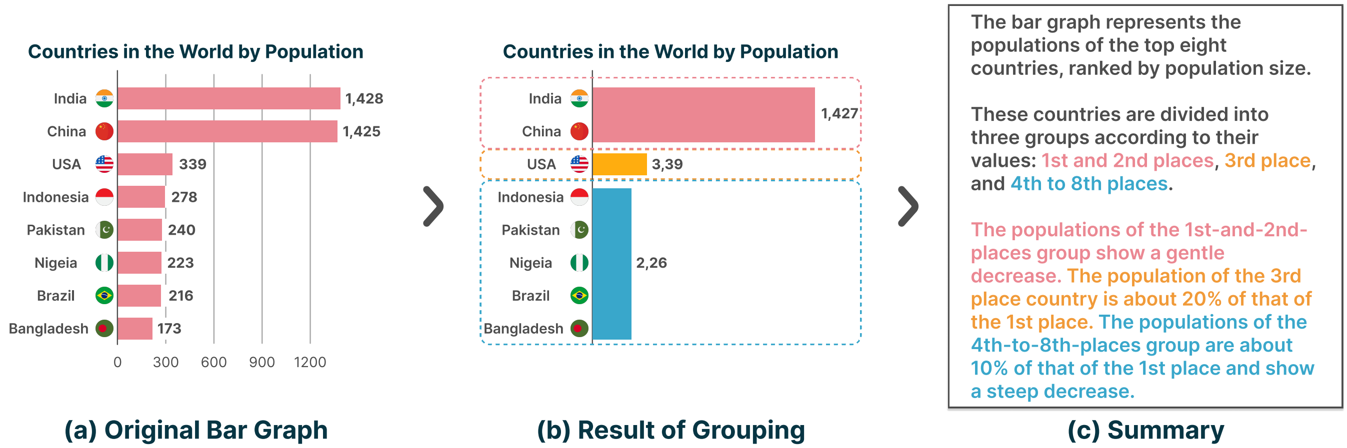


Figure 1: Overview of our summarization strategy. (a) The original bar graph about the ranking of the world population, arranged in descending order. (b) Clustering similar values into three groups. (c) Generated summary, which are automatically generated using a template-based method.

the summarization into a larger number of groups provides more detailed information. However, this requires a higher cognitive load in hearing, remembering, and recalling the information, which can cause error.

Therefore, we first investigate the effectiveness of bar grouping. We conducted a user study involving nine PVI (five blind and four with low vision). Participants were asked to recall numerical data in a bar graph after hearing a spoken description of the graph. The spoken description could be individual data points or a summarized description like Fig. 1(c). A statistical test revealed that summarization through bar grouping conveys information significantly more accurately compared to simply reading individual data points. Second, we explore its underlying reasons. We address this issue by proposing a cognitive error model. We define *observed error* as the discrepancy between the actual values of individual data points in a bar graph and the values as perceived by the user. Our model allows us to decompose the observed error into two components: errors caused by summarization and the cognitive load required for comprehension. Our model helps us understand the characteristics of the observed error.

The contributions of this paper are summarized below.

(1) We demonstrate the effectiveness of summarization through bar grouping in bar graphs: we found that properly grouped summarization can lead to more precise understanding because of less cognitive load.
(2) We propose an error model that explicitly accounts for the trade-off between errors caused by summarization and those caused by the cognitive load required for comprehension.

2 Methods

2.1 Generating Summary

The process for generating a summary involves four main steps:

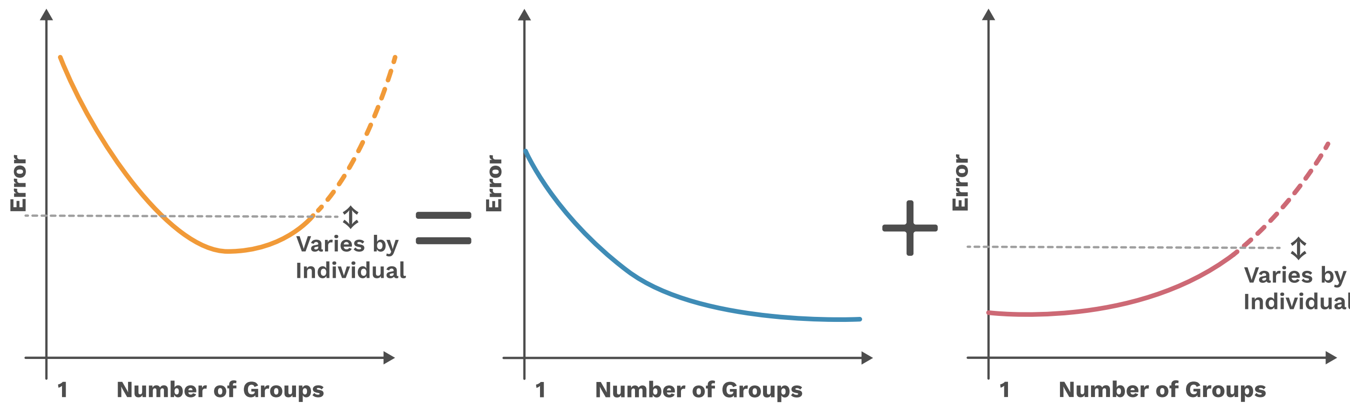
(1) **Data clustering into groups** using the Ward method [44] with Euclidean distance, with a predetermined target number of groups denoted as N.
(2) **Using relative ratios to the top rank** to describe the data points instead of their absolute values. This ratio is always rounded to be an integer. If it is 9.5 or higher, it is described as "almost the same as the top rank value."
(3) **Providing trend slopes within the groups.** A simple linear regression is performed within each group, and the regression coefficient determines whether the trend is gentle or steep. This analysis allows us to convey whether the trend within a group is significantly changing or stable.
(4) **Summary generation** is performed using a template-based method, drawing on existing research from ChartVi [27]. This research shows that an introductory message describing basic chart information, such as the graph title, type, and labels of the X and Y axes, should be presented first, as this information is important for PVI. Then, for each group, the ratio to the top rank and the trend within the group are explained in one sentence. The explanations of the ratios and trends are given separately for each group. A summarization example for three groups is shown in Fig. 1(c).

2.2 Error model

As shown in Fig. 2, we define following three errors.

(a) **Observed error**: the discrepancy between the actual values of individual data points and the values as perceived by the user.
(b) **Quantization error**: Errors resulting from information loss due to grouping, quantified as the sum of squared errors when approximating a bar graph with N line segments, as in a piecewise linear regression of a scatter plot.
(c) **Cognitive error**: Errors resulting from high cognitive load, making comprehension difficult.

The *quantization error* and *cognitive error* have a trade-off relationship. With a larger number of groups, the *quantization error* will be smaller because the summarization is detailed, but the *cognitive error* will be larger because PVI are more likely to miss graph content. Conversely, with a smaller number of groups, the *quantization error* will be larger because the summarization is rough, but the *cognitive error* will be smaller because it is easier to process. Finally, the *observed error* is the sum of these two kinds of errors, estimating how well the graph content is conveyed to PVI.



(a) Observed Error (b) Quantization Error (c) Cognitive Error

Figure 2: Overview of our error model: the *observed error* (a) is obtained by the *quantization error* (b) plus the *cognitive error* (c). (a) *Observed error* is directly measured in experiments. (b) *Quantization error* arises from summarization through bar grouping and depends on the number of groups. In this paper, we propose a method to calculate this. (c) *Cognitive error* cannot be directly measured, thus must be predicted. It is expected that under high cognitive load conditions, where the memory required to process the task exceeds the users' working memory capacity, typically occurring with a larger number of groups, the error becomes uncertain and difficult to predict. This is because the behavior of users can vary under such conditions.

3 Experiment

This experiment investigates how the number of groups, N, in summarization affects cognitive load and participants' estimation abilities. We ask the participants to listen to an explanation of the graph and then estimate the individual data points represented by the bars. The explanations are categorized into two cases: *non-summarization*, corresponding to simply reading individual data points, and *summarization* through bar grouping.

3.1 Study Design

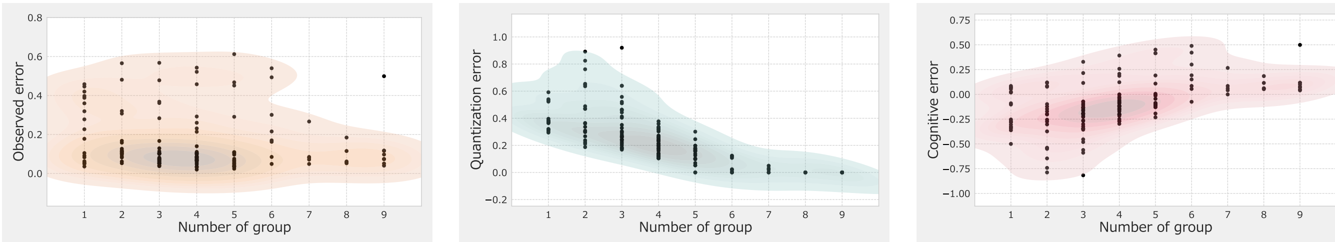
Nine PVI (five blind and four with low vision) participated in the user study. They included seven males and two females, with ages ranging from 34 to 62 years (AVE: 50.0, SD: 9.72). Each participant received a 2,000 yen gift card as a reward. Participants were asked to listen to the audio description of the graph once and then report the estimated individual data points. The experiment consisted of an instruction on the experiment, practice answering, and a task session where participants listened to graph descriptions and estimated individual data points. Finally, post-experiment interviews were conducted to complement our quantitative results and gain further insights into user needs. After the instruction and practicing, participants were asked to recall the values of each bar in the graph described.

In the *non-summarization* cases, ten individual data points of the graphs are read out. In the *summarization* cases, the summary for each graph is generated according to the process described in Section 2.1, with the randomly determined N. Since the value of the top-ranked bar is not included in the summary, it is informed after the summary is read out. In both cases, participants were required to provide the values for the bars from the second place onward, either as a relative percentage (e.g., 80%) with the top bar as 100%, or as the actual value of the bar on the graph (e.g., 1300 people). If they were unsure, they were instructed to respond with "I don't know." or an appropriate numerical estimate. All experiments were conducted online via Zoom and lasted approximately 90 minutes. The number of questions ranged from 11 to 22, (AVE: 20.3, SD: 3.759), depending on the progress of the experiment, and participants were allowed to take breaks between questions.

3.2 Result

The *observed error* was calculated for each graph as the sum of the absolute differences between the true values of the individual data points and those reported by the participant. Fig. 3(a) displays the distribution and density of the points representing all *observed errors* for all participants. This density visualization helps to better understand the shape of the distribution. Fig. 3(b) displays the distribution and density of the *quantization errors* calculated for all graphs examined by all participants. The number of points in these two graphs is the same. Following the proposed error model described in Section 2.2, for each graph, the *cognitive error* was calculated by subtracting the scaled *quantization error*, adjusted to match the range of the *observed error*, from the corresponding *observed error*. Fig. 3(c) displays the distribution and density of *cognitive errors*, which does not completely resemble Fig. 2(c), particularly in the right half of the graph. This is partially because, as mentioned in Fig. 2, we assume that the shape of the *cognitive error* curve can vary person-to-person or case-by-case. Therefore, further investigation with a larger number of participants is expected.

We compared the difference in *observed error* between the *non-summarization* and *summarization* cases as follows. First, in the *summarization* cases, for each participant, we identified the value of N that minimized the *observed error*, denoted as N_{min}. For most participants, $N = 4$ and $N = 5$ resulted in the smallest *observed error*. Exceptionally, for two participants, $N = 1$ resulted in the smallest *observed error*, despite having the largest *quantization error* due to a lack of explained information. Then, the *observed errors*



(a) Observed Error **(b) Quantization Error** **(c) Cognitive Error**

Figure 3: Three types of errors obtained in the experiment for all participants.

for $N_{\min}$ for each participant were compared with those from the *non-summarization* cases. A one-sided Mann-Whitney U test was used to assess significant differences between the two. The p-value was 0.039, which is below 0.05, indicating that *summarization* significantly reduced the *observed error* compared to *non-summarization*.

4 DISSCUSSION

4.1 Relationship with other studies

In the field of data visualization, specifically in generating summaries or alternative text for PVI, we found that explanations that are either too abstract or overly detailed in describing individual data points are not effective. These findings are not covered by sonification [1, 4, 7, 10, 12, 14, 15, 25, 31, 37, 41, 46, 47] or tactile graphics [6, 8, 11, 13, 18, 30, 34, 43] alone. Recent trends indicate an increasing need for multi-modal interfaces to further enhance accessibility.

The following papers are not directly related to grouping and graphs, but are particularly relevant to the field of Human-Computer Interaction (HCI) in terms of aiming at improving numerical comprehension. The use of perspective sentences [23, 35] explains numeric values in news stories, such as describing 7,700 pounds as "about the weight of a car." The use of rounded numbers [28] simplifies numerical information, such as presenting 3,792 as 4,000. The use of analogies [17, 24] contextualizes unfamiliar numbers by relating them to familiar geographic entities, like re-expressing 251,827 square miles as "about the size of Texas." Specially, research on rounded numbers addresses the trade-off between presenting rounded versus precise numbers. Although rounding results in an initial loss of precision, it can lead to greater accuracy in subsequent recall and estimation. Our proposed model may align with this concept by incorporating three types of errors.

4.2 Limitations

Our research investigated the effect of grouping on sorted bar graphs, with several notable limitations. Our findings cannot be directly applied to other graph types such as histograms, time series bar graphs, line graphs, and scatter plots. However, it is conceivable that these graphs could be approximated to a level of granularity where our findings might be applicable in textual representations.

5 CONCLUSSION

This paper contributed twofold. First, we demonstrated the effectiveness of summarization through bar grouping in bar graphs. We found that properly grouped summarization can lead to more precise understanding because of less cognitive load. We aimed to investigate the cognitive effects of grouping bar graph information for PVI. We found that graph explanations with a properly grouped summarization provide significantly more precise comprehension than reading individual data points. We verified the trade-off between errors caused by summarization and those caused by the cognitive load required for comprehension. It may seem obvious that overall summarizations are easier to recall than precise details, but our findings show that grouping can actually improve accessibility.

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