

# Explaining Unfamiliar Genomics Data Visualizations to a Blind Individual through Transitions

Thomas C. Smits\*  
Harvard Medical School

Sehi L'Yi†  
Harvard Medical School

Huyen N. Nguyen‡  
Harvard Medical School

Andrew P. Mar§  
Harvard Medical School  
University of California,  
Berkeley

Nils Gehlenborg¶  
Harvard Medical School

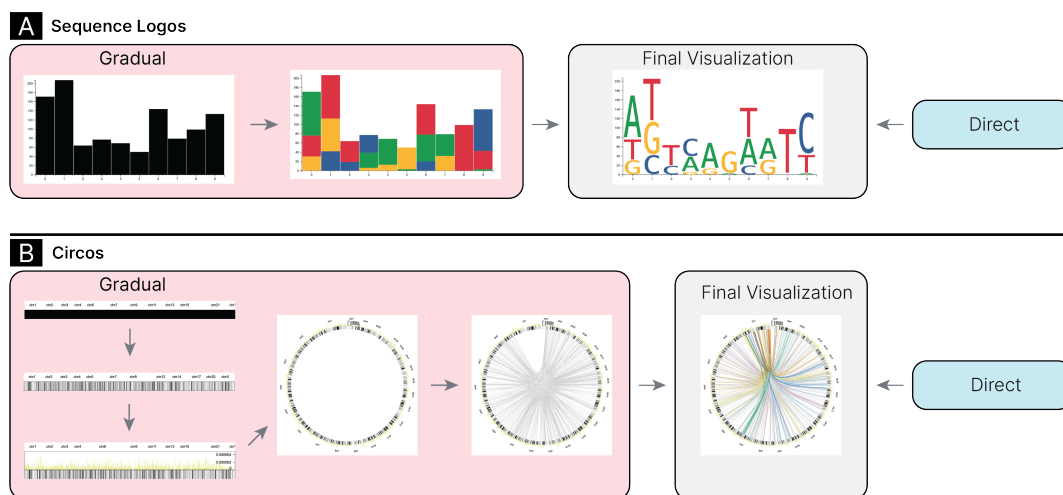


Figure 1: The *direct* and *gradual* approaches for introducing visualizations for sequence logos and Circos plots.

## ABSTRACT

The introduction of novel visualizations through animated transitions is a well-established practice in visualization research. In our preliminary exploratory study, we investigate whether this approach could effectively facilitate the introduction of new visualization types to blind and low-vision (BLV) individuals. Specifically, we present two approaches, *direct* and *gradual*, to a user who is blind and compare their potential usefulness. The direct approach involved a single, comprehensive description of the visual elements, while the gradual approach utilized a series of visualizations and transitions, starting from familiar visualization types known to the user and progressing to the final, novel visualization. We introduce two genomics visualizations, sequence logos and Circos plots, to the user with descriptions and then ask them to sketch the visualizations to reflect their understanding of the visual elements. Feedback from the user indicates that the gradual approach was easier to follow, suggesting that BLV individuals could benefit more from this method. We outline our design process and insights from the study, and highlight key considerations for future research directions.

**Index Terms:** Accessible Visualization, Perception & Cognition, Genomics, Transitions, Charts.

\*e-mail: tsmits@hms.harvard.edu

†e-mail: sehi.lyi@hms.harvard.edu

‡e-mail: huyen.nguyen@hms.harvard.edu

§e-mail: apmar@berkeley.edu

¶e-mail: nils@hms.harvard.edu

## 1 INTRODUCTION

Visualizations are abundantly used to convey messages regarding data [1, 14]. Over the years, numerous visualization types have been proposed to serve different purposes. Visualizations pose a challenge for people who are blind or have low vision (BLV) because they rely on visual perception, contrast, color, and navigation. Visualizations are often conveyed using alternative text descriptions and can also be converted into sound (sonification) or read with tactile devices and 3D-printed models [7]. Genomics is heavily data-driven and uses many specialized visualization types to make sense of complex genomics data [14]. However, without learning how genomics data visualization represents data, BLV students and researchers in genomics cannot utilize visualizations at all. Therefore, studying an effective method to explain unfamiliar visualization types to BLV people is critical.

Many approaches for introducing a novice to a visualization type have been tested in the visualization community. Various studies show that relating a novel visualization to known visualization types is beneficial [3, 15, 6]. These introductions can be done in a single step, explaining the differences, but various studies [3, 15] show that using a series of steps or morphing can increase the ease of understanding the novel visualization. However, there is a lack of proper approaches to introduce a visualization to a BLV audience. Considering the context of use for BLV individuals, it could be highly beneficial to advance the intersection of visualization and accessibility, bridging perspectives from both fields.

In this paper, we introduce the approach of introducing visualization types using a series of visualizations and transitions to the field of BLV research and conduct an introductory study with descriptions. To evaluate the participant's comprehension of the visual model, we ask them to sketch each visualization. We use a

similar setup and scoring system as Kim et al. [6] to compare the sketches to the actual visualization. Lastly, we outline various considerations and opportunities for further exploration of visualization methods for BLV individuals.

## 2 RELATED WORK

The visualization community has explored the usefulness of animated transitions, such as interpretability and learnability. Some efforts, such as Heer & Robertson [3], focus on transitions related to data insights. They presented a taxonomy of transition types as a reference. Other studies focussed on introducing new visualizations, such as Ruchikachorn & Mueller [15], who proposed the strategy of learning by analogies, using visual morphing to introduce an unfamiliar visualization type from a common visualization type. They presented the ‘in-betweens’ as an animation, an interactive visualization, and a series of pictures, to adhere to the apprehension principle [18].

Other efforts have focussed on how to best construct animated transitions. GraphScape [9], Gemini [8], and AniVis [11] are models and recommender systems for animated transitions that are based on similarities of visualizations. AniVis and Animated Vega-Lite [20] introduce models for the representation of transitions. Not all elements, such as particular visual elements and durations of transitions, are relevant to BLV research. However, other elements, such as ordering and structural changes, are helpful for our design.

In the accessibility research in the visualization field, various modalities are used to represent visualizations. Though promising for standard and simple charts, tactile and haptic options can be difficult to perceive, and details can be lost in sonification [7]. Printed 3D models are an additional method [4]. Given the complexity of genomics visualizations, we focus on descriptive texts, for which various recommendations exist [19, 5]. Lundgard & Satyanarayan [12] introduced a semantic model for levels of information in descriptions. We earlier focused on automating genomics descriptions [17].

We adopt the concept of animated transitions in order to explain unfamiliar visualization types to BLV users. Specifically, we explore the potential usefulness of explaining a visualization in sequence, such as how a visualization is composed or how a visualization is transferred from another familiar visualization. Similar to our work, Kim et al. [6] investigate various strategies for introducing BLV individuals to novel visualization types using descriptions. They tested the differences between using references to prior knowledge or no comparison, declarative or procedural knowledge, and abstract or concrete approaches. Our work is complementary: Kim et al. use various approaches in singular descriptions while our work explores the usage of a series of descriptions corresponding to a series of visualizations. It compares this to a single description of the final visualization.

## 3 PRELIMINARY EXPLORATORY STUDY

### 3.1 Approaches

In this preliminary exploratory study, a blind participant (co-author), following principles outlined in Smits et al. [17], was asked to review descriptions of visualizations and sketch them. Two different approaches were used (Fig. 1). In the *direct* approach, the visualization was directly described by its visual elements to the participant. In the *gradual* approach, the final visualization was constructed as a series of visualizations. It started with a type the participant was familiar with, and then visual elements were changed one at a time to transition to another visualization type. The participant was asked to sketch each intermediate visualization before hearing the following transition description. The descriptions of visual elements could still be enumerations of different elements in a visualization with multiple tracks. However, in the direct approach, each element was described directly as presented, whereas in the

gradual approach, elements were described in relation to another visualization.

### 3.2 Participant

The participant has a limited background in genomics. They have been fully blind since their late teens. Before designing our study, we identified the list of visualization types that are familiar to the participant since the descriptions of the gradual approach are designed based on the prior knowledge of the BLV individual. First, the participant was asked to list any visualization types they knew. They were then asked about a set of other visualization types known to the other authors without an in-depth explanation of the visualization. The participant was familiar with the following visualization types: flow chart, bar chart, scatter plot, pie chart, line charts, tables, Venn diagrams, trees or dendrograms, bubble chart, and density plot. The participant was unfamiliar with the following chart types: heatmap, circular bar chart, donut chart, area chart, histogram, violin plot, box plot, and node-link diagram. The participant was uncertain about stacked, grouped, and layered bar charts.

### 3.3 Visualization Examples

In this preliminary exploratory study, we use two visualizations: a sequence logos and a Circos plot. Sequence logos plots [16] are used to show the alignment of a genomic sequence by showing the frequencies of letters for each position. A sequence logos plot is similar to a stacked bar chart except that the vertical length of letters (e.g., A, T, G, C) encodes quantitative values instead of the vertical length of the bars. We selected the sequence logos as our first example. We deemed this a good starting point because it shares similarities with common visualizations such as the bar chart and stacked bar chart, so the transition series is limited to three steps. Circos plots [10] are circular visualizations with multiple views. There are many different types of Circos plots, as the visualization type is not well-defined. We utilize a simplified version of the genomics example by Krzywinski et al [10]. This Circos plot is used to show interactions and similarities between sequences in the genome. We chose the Circos plot as the second example, for we desired to explore the effect with a visualization with high complexity and circularity, as this concept is harder for BLV individuals [6].

Many resources on transition ordering focus on data transformations [9, 11]. We created the series on similar principles. We minimize the number of changing visual elements per transition. We split the creation of the sequence logos plot into three steps and the Circos plot into six steps (Fig. 1), where the participant was familiar with both first steps. All transitions belong to the *visualization change* and *data schema change* in Heer et al.’s taxonomy of transition types [3].

### 3.4 Procedure, Apparatus, and Tasks

The exploratory study was done in two remote sessions on Zoom. The participant accessed the tasks and descriptions through a custom website with the JAWS screen reader. The participant sketched on a tablet device (iPad) using a pen (Apple Pencil) with a sketching app (Notability). Both the screen of the laptop on the instruction website as well as the sketching app on the tablet were shared. The content from the instruction website is included in the Supplemental Materials.

For each visualization, the participant was given three tasks: 1) read the description, 2) verbalize what you think it looks like, and 3) sketch it out on the tablet and explain the sketch. Similar to [6], the participant could only read the description three times and could not switch back after starting to sketch. The direct approach was studied first followed by the gradual approach. As the color buttons of the sketch app were not properly labeled, the participant was helped to find different colors. During the direct and gradual approaches,

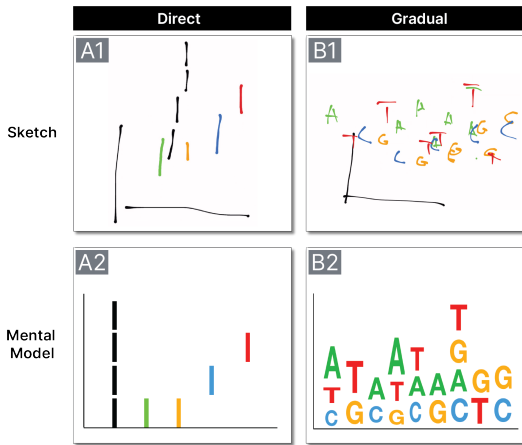


Figure 2: Sketches and mental model graphics for the sequence logos plot in the (A) direct and (B) gradual approach. The participant was asked to sketch the sequence logos plot on a tablet based on descriptions. (A1) The sketch after hearing the full description of sequence logos in the direct approach. (B1) The final sketch of sequence logos in the gradual approach. Other sketches in the intermediate steps of the gradual approach are included in the Supplemental Materials (Fig. S1). (A2 and B2) Reconstructed sketches that reflect the participant’s mental model based on the sketch and questions.

no feedback was given on the correctness of the visual elements of the sketches. In order to get a full comprehension of the mental model, the participant was asked to think out loud while sketching, and to explain his sketches. Questions were asked to clarify ambiguous visual elements. After both the direct and gradual approaches, each visualization was reviewed, and the participant was given feedback on visual elements and asked to sketch the visualizations that were previously incorrect. We refer to this phase as the *feedback* phase.

We created graphical representations of the participant’s mental model based on the sketch and accompanying explanation, as the sketch did not always look exactly as the participant meant due to them not being able to trace previously drawn lines.

### 3.5 Scoring System

We adapted the scoring approach from Kim et al. [6] to compare sketches based on the number of correct visual elements and similarity to the source visualization. The scores range between 0 and 5. Briefly, scores are given for a sketch without any correct visual element (0 out of 5), with one (1 out of 5), two (2 out of 5), or more (3 out of 5) correct elements, all correct elements but a slight error (4 out of 5), and all correct elements and resemblance to the original chart (5 out of 5). Where visual element in [6] refers only to “e.g., axes, mark and channel,” we extend this definition to composite visualizations, counting any correct element in any of the tracks composed (e.g., individual tracks in Circos), as well as how they are composed (e.g., superposition or juxtaposition). We omit color from the scores, as the participant was helped to select colors. Scores are included in the Supplemental Materials (Table S1).

### 3.6 Implementation

Sequence logos visualizations were created with D3 [1] by generating random data. Circos plot visualizations were created with Gosling [13]. To limit our influence on writing descriptions for each series, we created descriptions with GPT-3.5, an ad-

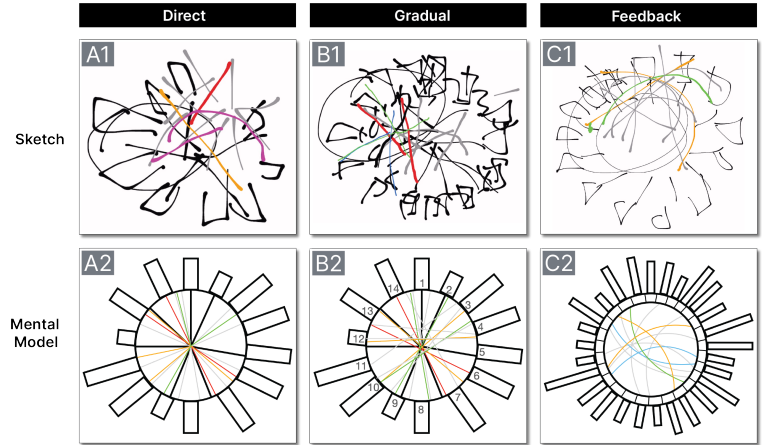


Figure 3: Sketches and mental model graphics for the Circos plot in the (A) direct and (B) gradual approach, and (C) feedback phase. Participant was asked to sketch the Circos plot on a tablet based on descriptions. (A1) The sketch after hearing the full description of Circos in the direct approach. (B1) The final sketch of Circos in the gradual approach. Other sketches in the intermediate steps of the gradual approach are included in the Supplemental Materials (Fig. S3). (C1) The final sketch of Circos during the feedback phase, where participant was given feedback on the correctness of visual elements. (A2, B2, and C2) Reconstructed sketches that reflect the participant’s mental model based on the sketch and questions.

vanced large language model capable of understanding and generating human-like text [2]. All prompts and responses are included in the Supplemental Materials. The source code for the website is available at <https://github.com/thomcsmits/transitioning-charts>. The website hosted with GitHub pages is available at <https://thomcsmits.github.io/transitioning-charts>.

## 4 RESULTS

### 4.1 Sequence Logos

The participant spent approximately eight minutes to read the description and five minutes to sketch for the direct approach, and on average four minutes for reading and four minutes for drawing for the gradual approach. In the direct approach (Fig. 2 A1 and A2), the participant could not get any visual element correct. This was scored 0 out of 5 using the scoring approach adapted from Kim et al. [6] (Table S1). In the direct approach, the participant had four black lines stacked on each other, with colored lines on the right aligning to one of these black lines. The description for the direct approach described bars rather than elongated letters, thus describing a stacked bar chart where the colored bars represent the letters. Therefore, it makes sense that the participant did not draw any letters. Still, the sketch did not resemble a stacked bar chart. The main confusion, as discussed in the feedback phase, was the phrasing of a “series of vertical bars that are stacked on top of each other,” as well as “each corresponding to a position along the x-axis.” Conversely, in the gradual approach (Fig. 2 B1 and B2), the participant had all visual elements correct (score 5 out of 5). Interestingly, the first two steps of the gradual approach (Fig. 1 A) had errors (Fig. S1). Regardless, the participant was able to draw the final step correctly. This suggests that other factors may influence the ability to get the correct mental model, such as the quality of the generated descriptions. The main confusion in the intermediate steps was regarding the difference between bars and lines. In order to transition from the bar chart to the stacked bar chart, they needed to split the bars into four segments. Splitting a line into four segments was

less intuitive and caused the confusion reflected in the sketch (Fig. S2) This also shows that although the participant is familiar with bar charts, it can still easily create confusion. Once cleared up, the participant could draw each step correctly and understand the connection between them. Since the gradual approach is discussed after the direct approach, the quality of the gradual approach can be influenced by prior knowledge from the direct approach. We believe this influence to be minimal since the sketch from the direct approach did not have any correct elements, and no feedback was given between the direct and gradual approach, but this should be approached differently in a future study, such as by presenting more participants with only one version and comparing between individuals. The participant found the gradual approach easier to follow. They also mentioned that it was unclear that some of the descriptions were declarative, explaining how it was constructed, and some were procedural, explaining how to draw this. *“I was kind of skipping around trying to figure out which of these instructions really tell me what to draw here and which of these are more in regards to how the chart is laid out.”*

## 4.2 Circos

The participant spent, on average, less than a minute reading the descriptions and between half a minute and three minutes sketching for both the direct and gradual approaches. This is much shorter than for the sequence logos, which can be explained by the familiarity with the tasks and the absence of data to read through. The participant got the bar chart correct for the direct approach (scored 1 out of 5) (Fig. 3 A1 and A2). Instead of a circular ideogram, the participant drew a pie chart. The straight gray lines all went to the middle (‘as the spokes of a bike wheel’). Some of the straight colored lines went to the middle, and some connected from one side to the other. The final sketch in the gradual approach was similar, with the bars and ideogram sketched the same (scored 2 out of 5) (Fig. 3 B1 and B2). However, the gray lines connected one side of the circle to another side. Though they were envisioned as straight, this is more true to the actual Circos plot, where these lines connect one segment of the ideogram to another in a curved way. The colored lines followed the gray lines and connected to two opposite sides of the circle. The hardest step of the gradual approach was turning the straight ideogram and bar chart into a circular representation. In the feedback phase (scored 4 out of 5) (Fig. 3 C1 and C2), various metaphors such as a watch strap, a disk, and the tire of a bike wheel, were used to convey this transition. The participant found it easiest to imagine the 2D rectangle to curve outward to a 3D circle, which was then flattened to 2D again. They found this the most tangible, as they found it hard to envision what it would be like in 2D. The different shades of the ideogram and curving lines through the middle remained complicated (Fig. 3 C1 and C2). Similar to the sequence logos, they found the gradual approach easier to follow, even if intermediate steps were incorrect. Additional sketches are included in the Supplemental Materials (Fig. S3 and S4).

## 5 DISCUSSION

In this preliminary exploratory study, we proposed to use transitions to introduce novel visualization types to BLV individuals. We compared the potential usefulness of a gradual approach to a direct approach with two examples for one participant. Comments from the participant suggest that BLV individuals could benefit from the gradual approach, though future work is needed to substantiate this suggestion.

The gradual approach can also help to understand the challenges in grasping a novel visualization. In the sequence logos example, we found out that the main challenge for the creation of a stacked bar chart was the difference between bars and lines, as the participant could not visualize how to split lines into different segments. In the Circos example, we observed that the transition between lin-

ear and circular layouts was mainly challenging. This is consistent with previous findings [6].

We did not provide any guidance except providing the descriptions during the direct and gradual phases. Only in the feedback phase, information on which visual elements were correct was given. With this feedback, the participant was generally able to sketch the visualizations better. An approach without feedback is still important to aid BLV individuals encountering visualizations in a non-educational setting.

One limitation of this study is that it tests the participant’s mental model using sketching, which may not be ideal since the participant does not typically use sketches to convey ideas, and a sketch from a blind individual may not completely reflect their understanding of a visualization due to inherent difficulty navigating the canvas/device surface. There may be more effective ways to test this model, such as with 3D objects. Alternatively, we can assess the interpretation of visualization through questions regarding data analysis tasks.

Another limitation is the variability in the generated descriptions. Descriptions were generated using similar prompts, yet the quality of the description varied, influencing the participants sketches. In the direct approach of the sequences logos example, the letter segments were described as bars, which explains the lack of letters in the sketch. The study could benefit from some authorial influence or templates, such that the final descriptions are more accurate and have similar quality.

A future study should include more participants and more examples. We used a within-subject design where the participant reviewed both the direct and gradual approaches of the same visualization. For a future study, we recommend a between-subject design, dividing the approaches for examples between participants, such that the first introduced approach does not influence the second approach. This study could be conducted in person based on modalities to facilitate different options for testing a participant’s mental model and better explanations of metaphors and directions. The various strategies of Kim et al. [6] can be combined into this study. In the future, the deconstruction of charts into a series of visualizations can also be automated.

The gradual approach is not limited to descriptions and could also be used in other modalities, such as 3D printing, where one could print a series of visualizations and explain the transitions and final visualization in this way. A future study can also include other modalities, such as 3D printing solely or prints in combination with descriptions.

The series for this study were designed using principles from previous research [9, 11]. However, these principles were derived from research with non-BLV individuals exclusively, which does not guarantee that these series are also optimal for non-BLV individuals. Extending this idea, the most optimal visualization type for a given task can differ for BLV and non-BLV individuals. To test this, we first need to be able to introduce these visualization types to BLV individuals, which was the purpose of this work.

## 6 CONCLUSION

In this preliminary exploratory study, we introduced an approach from the visualization community to the accessibility research in the visualization field. Initial feedback shows gradually introducing a visualization type using a series of visualizations could be promising. We outlined possibilities for future studies to solidify this approach.

## SUPPLEMENTAL MATERIALS

All descriptions, tasks, and visualizations used in the exploratory study are included in the Supplemental Materials, as well as the ChatGPT prompts and responses, additional sketches, and scores.

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## COMPETING INTERESTS

N.G. is a co-founder and equity owner of Datavisyn. The remaining authors declare no competing interests.

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