Towards Understanding the Authoring Strategy and Effectiveness of Visualization Sketches

Category: Research

ABSTRACT

Animated hand-drawing sketches are a common way to communicate concepts and information. Sketches are also used to query charts, interact with visualizations, or express rough designs. However, there are few works investigating how people manually create visualization sketches and whether animated sketches can help users understand charts. We first conduct a user study that collects the sketching processes of people with visualization knowledge and then summarize the patterns in the sketch order. Based on the sketch patterns, we conduct a between-subject study to evaluate whether animated sketches can improve users' performance of visualization tasks. We discuss the results of the user study and future work on evaluating the effectiveness of animated sketches.

Index Terms: Human-centered computing—Visualization—Visualization design and evaluation methods

1 INTRODUCTION

Sketch is a common way to communicate information even for children who can not write [22]. In the field of visualization, the sketch has been adopted as an interaction idiom for data queries [12] as well as input for generating visualization interfaces [16]. Prior research has demonstrated that visualization animations enhance the communication process by linking statistical charts [9], promoting attractiveness [20] and increasing engagement [6]. However, there is a lack of research explaining how different decomposition strategies of visualizations are involved in the sketch process of visualization charts and whether animated sketches can help readers understand visualization and improve their performance in conducting visualization tasks.

In order to answer this question, we first collected sketches of charts to elicit visualization sketching orders. We invite participants with different levels of expertise in visualization to increase the diversity of the results. We selected six types of charts, including four charts most commonly used for representing multi-dimensional data and two more complex charts for hierarchical and network data. We summarized the sketching patterns by annotating the sketches produced by these participants, focusing on both the overall order of chart components and chart elements inside chart components.

We then conducted a user study to evaluate the effectiveness of animated sketches in aiding users' comprehension of given visualizations. The order of the generated animated sketches is determined by the most frequently used strategies for each visualization type in the sketch collection stage. The effectiveness study was designed as a between-subject experiment, with participants randomly allocated into either the animated visualization group or the static visualization group. For each type of visualization, participants first learned the concept by viewing an animated or static visualization for the same duration, followed by completing tasks with three visualizations of the same type but visualizing different data. Although overall there is no significance found in the study with small exceptions, the results indicate further directions to investigate.

The contributions of this work include,

1. Summarized strategies for creating visualization sketches based on patterns derived from human-generated sketches;

2. Preliminary exploration of the effectiveness of animated visualization sketches in helping users conduct visualization tasks.

2 RELATED WORK

The present work relates to the evaluation of the effectiveness of animated visualizations and sketching visualizations from scratch. We will discuss them respectively in this section.

2.1 Evaluation on Animated Visualization

Animation has the potential to capture users' attention and engagement when viewing visualizations and performing tasks. Studies have shown that animated transitions between different statistical charts can aid in tracking items and help in retaining numerical values compared to static screenshots of statistical visualizations [9]. Furthermore, different temporal strategies of animation have been evaluated in the literature. The slow-in and slow-out strategy [7] has been found to conform to human perception and to support participants in achieving the highest accuracy. However, Chevalier et al. [5] found that staggering items can reduce the overlapping of marks but break the perception of common movement patterns of the same group of marks. In mobile visualizations, it is found that although animation attracts users, it can result in lower accuracy in perceiving trends in scatter plots than the method of showing visualization states with small multiples [3]. Animation can also aid in understanding data transformation and visualization learning and can be integrated into statistical analysis scripts to show data processing pipelines. The effectiveness of this type of animation used for visualization has been evaluated by researchers including Pu et al. [17], Kim et al. [10] and Ruchikachorn et al. [18].

These works aim to discover and address the negative visual effects of animation on visualization while promoting and enhancing its positive benefits. Different from them, our focus is on the helpful effects of animation on users' understanding of visualization and performance of conducting tasks, especially for those who have not met the visualization type before. Specifically, we explore how animation can aid in task completion by displaying the process of constructing a visualization from scratch.

2.2 Sketch of Visualization

Manual sketching is a widely used method that employs simple lines and shapes to convey complex meanings. It has practical applications in various fields, serving as a means of human-machine interaction and interpersonal communication. In visualization, manual sketching helps users query or interact with data. For example, the zenvisage system [19] allows users to quickly query visualizations by sketching line charts. Lee et al. [14] proposed an enhanced system that supports users' sensemaking process with sketching. Interactive visualization can also leverage sketching to reduce cognitive burden. In volume visualization, sketching can provide immediate visual feedback by directly manipulating regions based on volume characteristics [8]. Sketching facilitates fast and flexible design processes, allowing users to express their ideas quickly. Zheng et al. [24] explored the design space of visual note sketching with varying textual and visual contents and layouts. Bhargava et al. [2] had participants manually sketch data stories to summarize the process for visualization beginners. Xu et al. [23] tested how participants benefit from their proposed framework by having them sketch the opening of a visualization storytelling with a given guideline. Sketching visualizations can also encourage participants to explore the dataset. SketchVis [4] binds data with users' sketches of simple charts to support fast data exploration. SketchStory [11] and SketchInsight [13] further support storytelling and collaborative exploration through sketch interaction. DataInk [21] is a visualization authoring system that replaces traditional predefined marks and templates with sketched marks by humans for better expressiveness and attractiveness. Sketching can also be used in the data quality inspection process. Data hunches [15] allows experts to sketch on a visualization to express their opinion on data problems.

Rather than focusing on sketch as interaction, we design user experiments to explore the extent to which animations composed of such sketches assist novices in understanding visualizations.

3 Sketch Sequences Collection

We conducted a preliminary study to investigate the strategy used by participants in sketching visualizations, with a specific focus on their sketching sequences. Participants are provided with one demo chart to get familiar with the system and six visualization charts to sketch as if they are introducing the concept to people who have not met this visualization type before. We have implemented an online system that displays the target visualization chart and allows participants to draw sketches on it. Participants draw the sketches in the system on an iPad.

3.1 Stimuli and Data

The six visualization charts used in this study were created using datasets sampled from real-world datasets. These charts cover both basic visualizations and more complex ones. The four basic types of visualizations include bar charts, stacked bar charts, line charts, and scatter plots, which are the most commonly used charts on the web [1]. The underlying data of the four types of charts are sampled from a weather dataset of New York. The other two more complex visualizations are sunburst plots and Sankey diagrams. A population dataset was applied for the sunburst plot, and an international trade dataset was used for the Sankey diagram. The topics, including weather, population, and trade, are widely known, and all participants are expected to be familiar with their semantics, eliminating the need for extra effort to understand the meanings of attributes in visualizations.

To make the sketch process easier, color encoding was intentionally excluded in the visualizations provided. Therefore, all six visualization charts provided applied channels such as shapes and annotations to distinguish different categories in place of the color channel.

3.2 Participants

We involved 33 participants who were undergraduate students, graduate students, or professors from two universities. The age of the participants ranges from 20 to 32. The participants have diverse levels of visualization expertise, ranging from at least having taken one visualization class to graduated Masters and Doctors in the visualization field.

3.3 Procedure

For each visualization chart, participants were first instructed to read the chart. They were then asked to draw sketches of the visualization as if they were introducing it to people who had not met this chart type before. During this process, their thoughts were recorded using the think-aloud method.

Participants were allowed to use abbreviations to replace the long texts. However, it was emphasized that all visualization components and elements, particularly elements like titles, legends, and axis ticks that were easy to overlook during the drawing process, should be included in their sketches.

Throughout the study, participants were presented with seven visualizations, including one demonstration case and six formal cases. An experiment system was implemented for this study, and

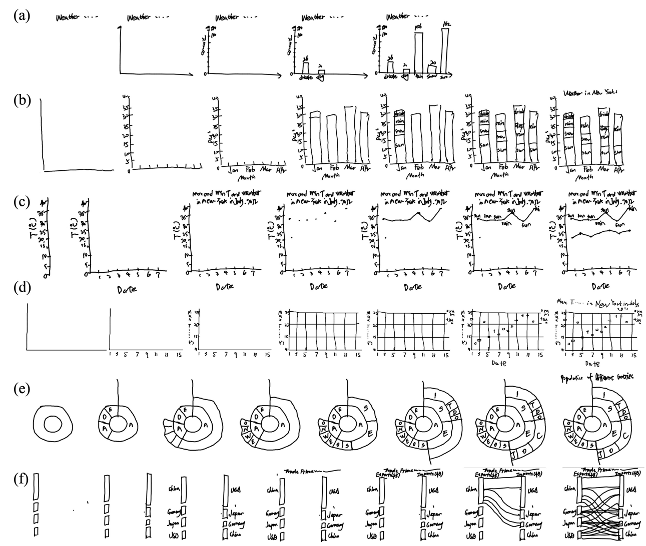

Figure 1: Sketches of six kinds of charts from different participants in the sketch collection stage. (a) Drawing the bar chart by first writing the title and sketching the lines of both axes. The X axis ticks were sketched along with the bars and text labels. (b) Drawing the stacked bar chart by first sketching the outline of the bars and then dividing them into stacked bars. (c) Drawing the line chart by first sketching the points and then connecting them with lines. (d) Drawing the point marks in a scatter plot and putting the legend to the last stage. (e) Drawing the sunburst plot from the inner level to the outer level. (f) Sketching all the nodes first and then connecting them with the curves.

participants accessed the experiment webpage using an iPad. The system displayed the visualization on the left of the webpage and provided the sketch area on the right. Participants were asked to draw the sketches using an Apple pencil. The system automatically recorded participants' answers and sketching sequences.

3.4 Overall Strategies of Visualization Sketch

In our study, we emphasized the inclusion of all visual components in participants' sketches. However, there were instances where certain elements, such as titles, legends, or other components, were missing from the sketches. Due to the incomplete nature of these sketches, we excluded those participants from our analysis. We collected 26 charts for each chart type from the rest of the participants. Fig. 1 shows example sketches drawn by different participants.

We first analyzed the collected sketch sequences by labeling the sketch order of semantic chart components. These chart components include the *Title*, *Axis*, *Legend*, and *Data Marks* which have distinct visual formations across various charts. Additionally, we also annotated the hierarchical structures in which users sketched the *Data Marks*. For instance, the *Data Marks* of the line chart consist of *Points* and *Line Segments* that connect the *Points*. Participants may draw all the points and link them using line segments. Others may draw the points and lines in turn to link the points immediately after they are drawn. Two of the authors annotate the sketch sequences of the chart components and discuss to refine the annotation results.

To better represent these sketch sequences, we created flow charts where each node represents one component or the sketch order of *Data Marks*, as shown in Fig. 2. These sequences began with the 'start' node and then progressed to the relevant component nodes. The numerical values indicate the number of participants whose sequences followed a given path. We did not include auxiliary lines or marks, such as grid lines, drawn by participants to align marks with axes. We introduce the sketch order summarized for the stacked

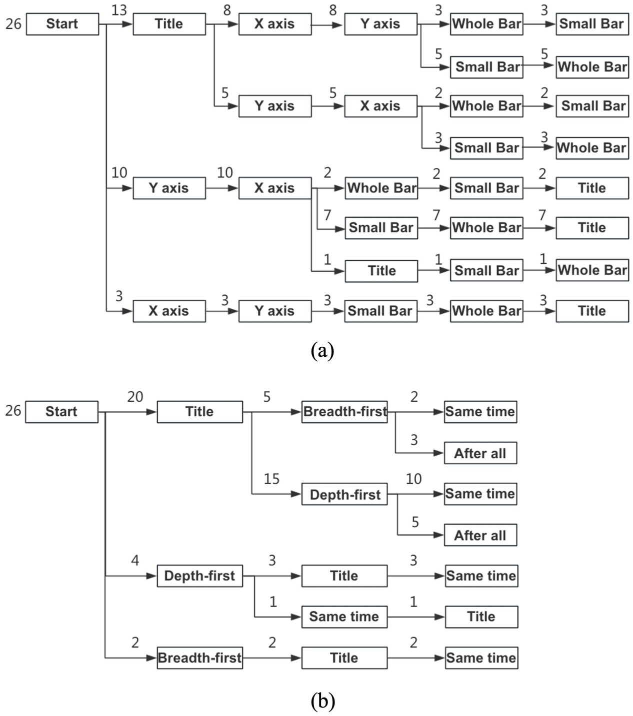

Figure 2: The sketch order of chart components of the stacked bar chart (a) and the sunburst plot (b). The numbers over links represent how many participants take the sketch order.

bar charts and the sunburst plots in the following paragraphs. The results of other visualization types are included in the supplementary material.

Stacked Bars can be sketched using two main strategies. The first approach involves drawing the entire bar before dividing it into smaller stacked rectangles, while the second approach entails sketching the smaller bars separately before integrating them into a whole bar. These two strategies have been labeled in our study as *Whole Bar* to *Small Bar* and *Small Bar* to *Whole Bar*, respectively, and are depicted in Fig. 2 (a). X and Y axes are often sketched together, but there is no significant preference found in their relative order. However, participants always draw the axes before the data marks, showing that they prefer to draw marks after determining the meaning of the position channel. The position of the *title* in the sketch sequence is relatively random compared with *Axis* and *Marks*.

In the case of sunburst plot sketches, we observed two strategies for drawing segments at different levels. As sunburst plots visualize hierarchical data and contain multiple levels of segments, the two sketch strategies differ in their traversing order. Participants taking the first strategy would draw all the segments at the same level. Then they drew segments at the following levels, as if they traversed the hierarchical structures in the breadth-first order. The other participants would draw one sub-tree from a root node a and then consider another node b at the same level as a in a depth-first order. We have labeled these strategies as *Breadth-first* for the breadth-first sketching order and *Depth-first* for the depth-first strategy in Fig. 2 (b). Moreover, we found that there are two approaches to adding text labels for these segments. Some participants label the segments immediately after sketching them, while others complete all segments before labeling them. These labeling strategies have been denoted as *Same time* and *After all*, respectively.

3.5 Strategies of Visualization Sketch Inside Components

After examining the sketch order of visualization components, we also further analyzed the visualization element inside each component and summarized the sketch strategy inside each chart component.

Title: In the study, there is only one main title in each chart. Most participants put the title before or after the rest of the visualizations, which means participants either introduce the title to let the audience know the background before going to other parts or think the title provides only complementary information after they introduce the 'main area' of the chart.

Axes: When drawing an axis, participants all draw the axis line first. Some participants would like to draw the axis lines of the X axis and the Y axis first to define the chart area. With regard to ticks and labels, some participants draw pairs of ticks and labels consecutively, while others draw all the ticks before the labels. The titles of the axes are generally drawn either before or after the ticks and labels. We do not find a particular preference for which axis to draw first.

Legend: In the study, only the scatter plot contains the legend component. Most of the participants draw pairs of legend icons and labels consecutively. Only a small portion of participants take other paths like drawing labels before legend icons or drawing all the icons before drawing the labels. Additionally, some participants put the legend before or after all data marks, while others prefer drawing data marks of one category right after drawing legend marks representing this category.

Data Marks: In the bar chart, stacked bar chart, line chart, and scatter plot, most of the participants tend to draw the marks from left to right or vice versa. However, some participants thought it would be useful to draw marks based on data characteristics. For example, they will draw the bars from the maximum value to the minimum value. For visualization containing hierarchical information, some participants draw the overall mark and then divide them into different parts while others prefer to combine small parts to get the grouped mark. For example, in the stacked bar chart, participants will draw bars based on a different order of attributes to group the bars. They would draw all bars inside a stacked bar, or draw the bars with the same categorical value together. In the line chart with multiple lines, participants need to consider the point and lines connecting points. Some participants will explicitly draw all the points inside one line and then connect them with lines. Others will draw the lines from the beginning date to the final date.

Data Marks + Axes: When an axis encodes a categorical attribute like the X axis in the bar chart or a temporal attribute like the X axis in the line chart, axis ticks, axis labels, and data marks can be grouped by the attribute value. For example, some participants would draw the tuple of axis tick, bar, and axis label with the same X position sequentially in a bar chart.

Since there can be many possible paths when combining different components to sketch the visualization between users, we decided to follow the most adopted path for each type of visualization. We applied those paths as standard sketch sequences in the user experiment in the next section.

4 Study 2: Effectiveness Experiment

We then conducted the effectiveness experiment to evaluate the potential benefits of showcasing the visualization sketching process from scratch to enhance audiences' understanding of charts and the performance of conducting tasks. To this end, we generated the following hypothesis:

- **H1**: Animated visualization sketches improve users' accuracy when answering questions on visualizations they have not met before.

- **H2**: Animated visualization sketches reduce users' completion time when answering questions on visualizations they have not met before.

To verify those two hypotheses, we planned to conduct a between-subject experiments. In the experiment, the experimental group was provided with animated chart sketches, while the control group was provided with only static charts. Then, both groups were asked to answer corresponding questions about the visualization, and their answers and completion time would be recorded as the key metrics of their understanding of visualizations.

4.1 Stimuli and Tasks

We aimed to test the effectiveness of animated chart sketches on the visualization understanding of participants who had not met charts of the same type before. Based on the participants' experience of visualization, we conducted the study focusing on two visualization types, namely, the sunburst plot and the Sankey diagram. These two types of visualization were less familiar to the participants we invited.

We prepared four visualization charts for each selected visualization type. The first one served as demos, while the other three charts were used as tests. All visualization instances were generated using distinct synthesized datasets with different topics. For each type of visualization, the sunburst plot or the Sankey diagram, we assigned tasks that needed multi-step analysis. Specifically, participants were required to read the values from charts, understand the relations between data structure and visual encoding, and do comparisons before getting the correct answers. For example, for one of the Sankey diagrams, participants were asked to find out the region that has the most similar proportion of energy allocated to another given region. They first had to understand the relation of input and output of the Sankey data, and then make comparisons between different allocation proportions to find out the correct answer. In this way, we increased the complexity of questions assigned to visualizations.

We generated the animated sketches shown in the demo process based on the summarized sketch strategies we got in the sketch collection stage. The generated animations, containing the sketch sequences of both the sunburst plot and the Sankey diagram, are shown in the supplementary material. During the test processes, no more animations were shown. All participants were provided with only static visualizations to answer the questions. To maintain consistency of visualization style, the animated visualization sketches and the static visualizations were all rendered in sketch style.

4.2 Participants

In total, 67 participants were recruited for the experiment through online forums from two universities. None of the participants in this experiment had previously participated in the sketch collection stage. Before the experiment, participants completed a demographics questionnaire. Upon completion of corresponding tasks of one chart type, they were asked to fill in their experience of this chart type. Only participants without prior knowledge of the chart type will be included in the result analysis. The experiment was conducted online, and participants were instructed not to seek external assistance.

4.3 Procedure

We conducted a between-subjects experiment to verify our hypotheses on the effectiveness of animated sketches (**H1** and **H2**). The participants were assigned at random to either the experimental group, which received animated sketches at the demo stage, or the control group, which was given static visualizations.

All participants would first go through the demo stage, where they were provided with animated sketches or static visualizations based on their group. The duration of this stage was set as the duration of the animation of the demo chart for both groups.

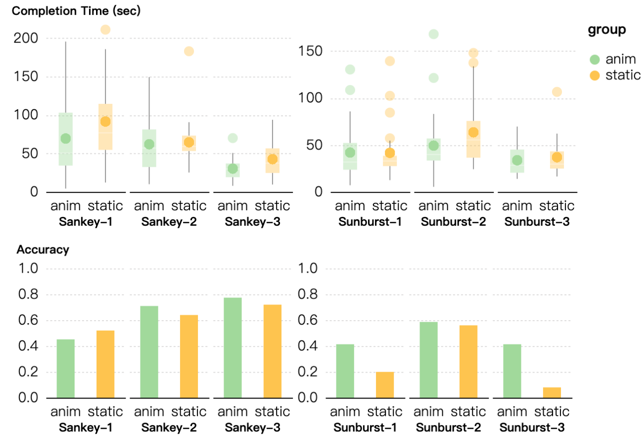

Figure 3: The boxplot shows the distribution of completion time of each experiment group conducting the 6 tasks. The non-opaque points show the mean completion time of each group and the white strip lines show the median completion time. The bar chart below shows the accuracy of participants conducting tasks on different charts.

Following the demo stage, participants were instructed that they would be presented with three new visualization charts and one related task for each chart. The newly shown charts were the same type of the visualization in the demo stage but visualized different data. In this test stage, both groups were provided with only static visualizations.

After the whole study, we provided extra questions to confirm whether users had met with the visualizations before they attended the experiment.

All participants would go through two types of visualizations continuously, including the sunburst plots and the Sankey diagrams. We developed an experimental system in which all stages of the study were conducted on a web page.

4.4 Experiment Results

According to questions provided to participants on their familiarity with certain types of visualizations, we excluded those who already had a prior understanding of the visualizations before the experiment, since they could not be treated as novices anymore. As a result, we finally obtained results from 56 participants (31 in the animated visualization group and 25 in the static visualization group) for the Sankey diagram and 54 participants (29 in the animated visualization group and 25 in the static visualization group) for the sunburst plot.

We calculated the mean completion time and accuracy of the two experiment groups for the six tasks. The significance of the difference in completion time for each task was computed using the one-way ANOVA method, while the significance of accuracy was determined using the Chi-square test, with the correct answer assigned a value of 1 and the incorrect answer assigned a value of 0. The time distribution and accuracy of participants completing the six tasks are also depicted in Fig. 3.

In regards to the Sankey diagram, the results indicate that there were no significant differences in the completion time for task *Sankey-1* ($F(1,54) = 2.3837, p = 0.1284$) and *Sankey-2* ($F(1,54) = 0.0795, p = 0.7791$), but in the third task *Sankey-3*, the completion time of the animated visualization group was significantly lower than that of the static visualization group ($F(1,54) = 6.1825, p = 0.0160 < 0.05$). Overall, there is no significance in the effect on the completion time. However, the results of the third task may suggest that the animated sketches of the Sankey diagram were helpful to participants in identifying complex node-link structures with clutters and crossovers more efficiently. We need further take the impact of visualization and data complexity into consideration in the future experiment design. No significant differences were found in the accuracy, which may indicate that participants could infer the meaning of the Sankey diagram based on their common knowledge, and the animated sketches can hardly further help in conducting the tasks correctly.

Our analysis suggests that no significant differences were found in the completion time for the sunburst plot (*Sunburst-1*: $F(1,52) = 0.0014, p = 0.9701$, *Sunburst-2*: $F(1,52) = 2.3409, p = 0.1321$, *Sunburst-3*: $F(1,52) = 0.4185, p = 0.5205$). There was no significance in accuracy found in the first chart (*Sunburst-1*: $accuracy_{animated} = 0.4138, accuracy_{static} = 0.2, p = 0.1636$) and the second chart (*Sunburst-2*: $accuracy_{animated} = 0.5862, accuracy_{static} = 0.56, p = 1.0$). In the third task (*Sunburst-3*), however, the animated visualization group exhibited significantly higher accuracy compared to the static visualization group ($accuracy_{animated} = 0.4138, accuracy_{static} = 0.08, p = 0.0132 < 0.05$). The main difference between the third chart and the other charts is that some leaves are hidden intentionally to test whether the users can become aware of the absent leaves. This suggests that animated sketches may aid participants in comprehending information that is not directly shown in the charts.

Overall, our hypotheses on the effectiveness of the animated sketches (**H1** and **H2**) were partially rejected based on the result of the formal study. The results show that after watching the sketch animations on the sunburst plot and Sankey diagram, there is no significance found in the accuracy and the completion time except for some occasional cases.

There are several reasons that would lead to this partial rejection. One important reason is that the complexity of charts and tasks may have an influence on the effectiveness of animation, but the experiment design has not controlled these attributes. Though this study can not generate precise conclusions on exactly under which types of visualizations and which kinds of tasks will the animated sketches enhance novices' comprehension, it demonstrates the potential that those animations can help with understanding on certain occasions.

5 Discussion and Future Work

In this work, we collect sketches from people with different levels of visualization expertise, ranging from taking one visualization class to having worked on visualization research for several years. However, the visualization sketches collected are still at a small scale. By collecting visualization sketches from more people, we can create a dataset of visualization sketches. The dataset can support analysis of how people understand visualizations and how they communicate visualization to other people. In this work, we summarized the sketch patterns to synthesize training data. With a larger-scale visualization sketch dataset, we can directly learn the animated sketches from the dataset. In the first part of this work, we asked participants to sketch visualizations as if they were teaching others about the encoding of the charts. However, people may change their sketch orders and strategies if they are given different data tasks. For example, users with an extreme finding task may tend to draw the highest bar in a bar chart instead of drawing bars from left to right.

We conduct a between-subject user experiment to evaluate whether the animated visualization sketches can help users conduct visualization tasks more accurately and faster. Most participants in the experiment are familiar with charts like bar charts, line charts, and scatter plots, thus we decided to include only the Sankey diagram and the sunburst plot in the experiment. Although we do not find overall significant differences in the accuracy and completion time in both chart types, we do find occasions when there is significance in results. For example, in the design of the third sunburst plot and the task related to it, we intentionally make some leaves absent so that the participants need to understand the structure of the sunburst plot to correctly determine whether the answer can be found in the chart. We think it is possible that animated visualization sketches can help users who have not met a certain chart type before to understand the structure and the hierarchy of a complex chart. In future work, we plan to further investigate whether animated sketches can help understand more complex visualizations.

6 Conclusion

We first collected human-drawn sketches of charts from participants with different levels of visualization expertise. Then we summarized the sketch patterns of different charts and found common strategies for the sketch order of chart components and detailed patterns inside each component. We also conduct a user experiment to evaluate the effectiveness of the sketch animation and propose future directions for evaluation of animated chart sketches.

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