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Toward Understanding Representation Methods in Visualization Recommendations through Scatterplot Construction Tasks

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Abstract

Most visualization recommendation systems predominantly rely on graphical previews to describe alternative visual encodings. However, since InfoVis novices are not familiar with visual representations (e.g., interpretation barriers [GTS10]), novices might have difficulty understanding and choosing recommended visual encodings. As an initial step toward understanding effective representation methods for visualization recommendations, we investigate the effectiveness of three representation methods (i.e., previews, animated transitions, and textual descriptions) under scatterplot construction tasks. Our results show how different representations individually and cooperatively help users understand and choose recommended visualizations, for example, by supporting their expect-and-confirm process. Based on our study results, we discuss design implications for visualization recommendation interfaces.

CCS Concepts

•***Human-centered computing*** → *Visualization; User studies;*

1. Introduction

As information visualization (InfoVis) becomes mainstream technologies, the InfoVis community is paying more attention to non-expert users who are unfamiliar with either visual representations or visualization construction processes. Among the most prominent research and development efforts in this regard is visual encoding recommendations for InfoVis novices. Recommended Charts in Microsoft Excel [Exc18] and Show Me in Tableau [Tab18] are typical examples of visualization interfaces for recommending visual encoding alternatives based on user-selected data fields. With the recent evolution of data analysis techniques such as machine learning and deep learning, recommendation models can become even more effective, for example, by using the ranked effectiveness of visual encodings from visual perception experiments [MWN*18].

In contrast to the actively researched analytic side of visualization recommendations, research on user interface designs for more effective and understandable depictions about the suggested visual mappings has received relatively less attention in the InfoVis community. Most recommendation systems predominantly rely on graphical previews to describe alternative visual encodings [Exc18, WQM*17, WMA*16, VRM*15, KHPA12, GW09, KHPA12, EB11]. However, because InfoVis novices are known to have difficulties in understanding visual representations in general [GTS10], we cannot expect novices to fully understand suggested visual encodings with the graphical previews. Misunderstanding the suggestions might hider novices from producing the visual encodings they envision. To facilitate novices' learning about new visual encodings, Grammel et al. [GTS10] suggested using in-depth textual descriptions to explain about visual encodings such as the advantages and disadvantages of using new visual encodings. However, the effectiveness of such alternative methods for describing the recommended visual encodings (e.g., in-depth textual descriptions) have not been explored in previous studies.

As an initial step toward understanding the effectiveness of different representation methods for visualization recommendations, we conducted a qualitative user study with InfoVis novices under scatterplot construction tasks. By reviewing studies related to visualization recommendations and InfoVis novices, we came up with three primary representations: previews, animated transitions, and textual descriptions. We then designed a prototype of a recommendation interface for the user study using three representation methods. Through the user study, we found that although previews remained the most preferred representations, novices still relied on textual representations. Our findings also illustrate that combining multiple representations can help users better understand the recommendations by supporting them expect and confirm about the behaviors of recommendations. Based on the findings, we present implications for designing interfaces for effective visualization recommendations for novices.

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2. Related Work

We review literature relevant to our study regarding visualization recommendation interfaces and studies for understanding InfoVis novices.

2.1. Visualization Recommendation Interfaces

Depending on the purpose of recommendations, interfaces may vary to some degree, but overall, recent visualization systems tend to use similar recommendation interfaces. In terms of layout, most systems use a gallery-based layout either showing multiple recommendations at once for easy comparison between alternatives [WMA*16, WQM*17, Exc18, MHS07, WW10, VRM*15, vdEvW13, BGV16, GW09, KHPA12, SKC*11, DW14, EB11] or a single recommendation while enabling easy exploration of alternatives [JLLS17, SS05]. For representing individual recommendations, previews hold a dominant position [Exc18, WQM*17, WMA*16, VRM*15, KHPA12, GW09, EB11], while simple textual descriptions are sometimes used with the preview [MHS07, JLLS17, WW10, vdEvW13, SKC*11, DW14, SS05]. We identified two types of previews in recommendation interfaces: abstract thumbnails and actual visualization results. As thumbnail previews provide abstract information about the recommended visualization, they are used to show chart types (e.g., Show Me in Tableau [MHS07]). Although abstract thumbnails have a performance advantage for large data because they do not require detailed chart rendering, actual visualization results tend to be used for data-level and encoding-level recommendations (e.g., recommendations for using different data fields in the same chart type) for providing more detailed information.

In contrast, textual descriptions are used to provide additional information such as chart types (e.g., Bar Chart) [EB11, GW09, BGV16, Exc18], data fields used in recommended visualizations (e.g., "IMDB Rating vs Rotten Tomatoes Rating") [KHPA12, VRM*15, WQM*17, WMA*16], or more details about when to use a specific type of visualization [Exc18] or what it is [WQM*17, WMA*16]. Based on an exploratory study with InfoVis novices, Grammel et al. [GTS10] claim that, to help users better understand recommendations, more in-depth explanations about the recommendations should be provided, including the advantages and disadvantages of using them. However, the effectiveness of textual descriptions in novices' visualization construction process has not been previously explored. In our study, we examined the effectiveness of three different representation methods for recommendations including the in-depth textual descriptions suggested by Grammel et al.

2.2. Understanding InfoVis Novices

The InfoVis community has focused on understanding novices by performing various user studies. Using sketching [WHC15] or tangible building blocks [HJC14], researchers conducted exploratory studies to understand how novices transform data into visualizations. Smuts et al. [SSC15] and Grammel and Storey [GS10] suggested several guidelines for supporting novices in designing visualization tools through user studies. Through an observation study, Grammel et al. [GTS10] identified three challenges novices confront during a visualization construction process: *data selection*, *visual mapping*, and *interpretation barriers*. Motivated by Grammel et al.'s work, we presumed that novices might find it difficult to understand recommendations only with the most common representation (i.e., a preview for the result visualization) because novices have difficulties in interpreting visualizations (i.e., *interpretation barrier*). In our study, we used two more representation methods (i.e., animated transitions and textual descriptions) to explore how novices use recommendations with different representation methods.

Other studies compared visualization tools to understand how novices construct visualizations with different interfaces. Méndez et al. [MHN17] compared novices' visualization construction process in two different types of interfaces: bottom-up approach (i.e., iVoLVER [MNV16]) and top-down approach (i.e., Tableau [Tab18]). Jo et al. [JLLS17] compared three visualization tools (i.e., TouchPivot, PivotTable of Microsoft Excel [Exc18], and Tableau [Tab18]) through controlled user studies and identified several hurdles for novices in the visualization tools. We go a step further to broaden the understanding of InfoVis novices with various recommendation representations through scatterplot construction tasks.

3. Prototype Design

We designed a prototype of a recommendation interface for our user study to understand how novices understand and choose suggested visual encodings with different representation methods during the visualization construction process.

To more efficiently identify the effects of different representation methods, we encouraged participants to actively use recommendations within the limited time of the user study. For this purpose, we assumed scenarios in which users perform goal-oriented visual analysis tasks [GTS10] with recommendations in our prototype assisting them to accomplish sub-goals to complete the main goal.

3.1. Visualization Goals

We defined the participants' main goal as constructing scatterplots to complete major scatterplot-specific analysis tasks [SG18]. The reasons for using the scatterplot visualization are that the scatterplot is one of the most familiar visualizations to novices [LKK17] and that it has been widely adopted in visual exploration and recommendation systems (e.g., [WQM*17, Tab18, DW14]). We defined the users' sub-goals as alleviating over-plotting problems in scatterplots, as overdrawing in visualizations is one of the most well-known problems in the InfoVis community and is frequently addressed in InfoVis literature for novices (e.g., [Few09]). We designed a recommendation interface for supporting the sub-goals (clutter reduction), and the main goals (scatterplot tasks) were provided as the main tasks in our study (i.e., participants had to use recommendations to complete their tasks in the study).

3.2. Recommendations

We designed seven scatterplot clutter reduction strategies for visualization recommendations in our prototype by referring to the clutter reduction taxonomies [ED07, Few09] (Figure 1): (B) *Filter By*

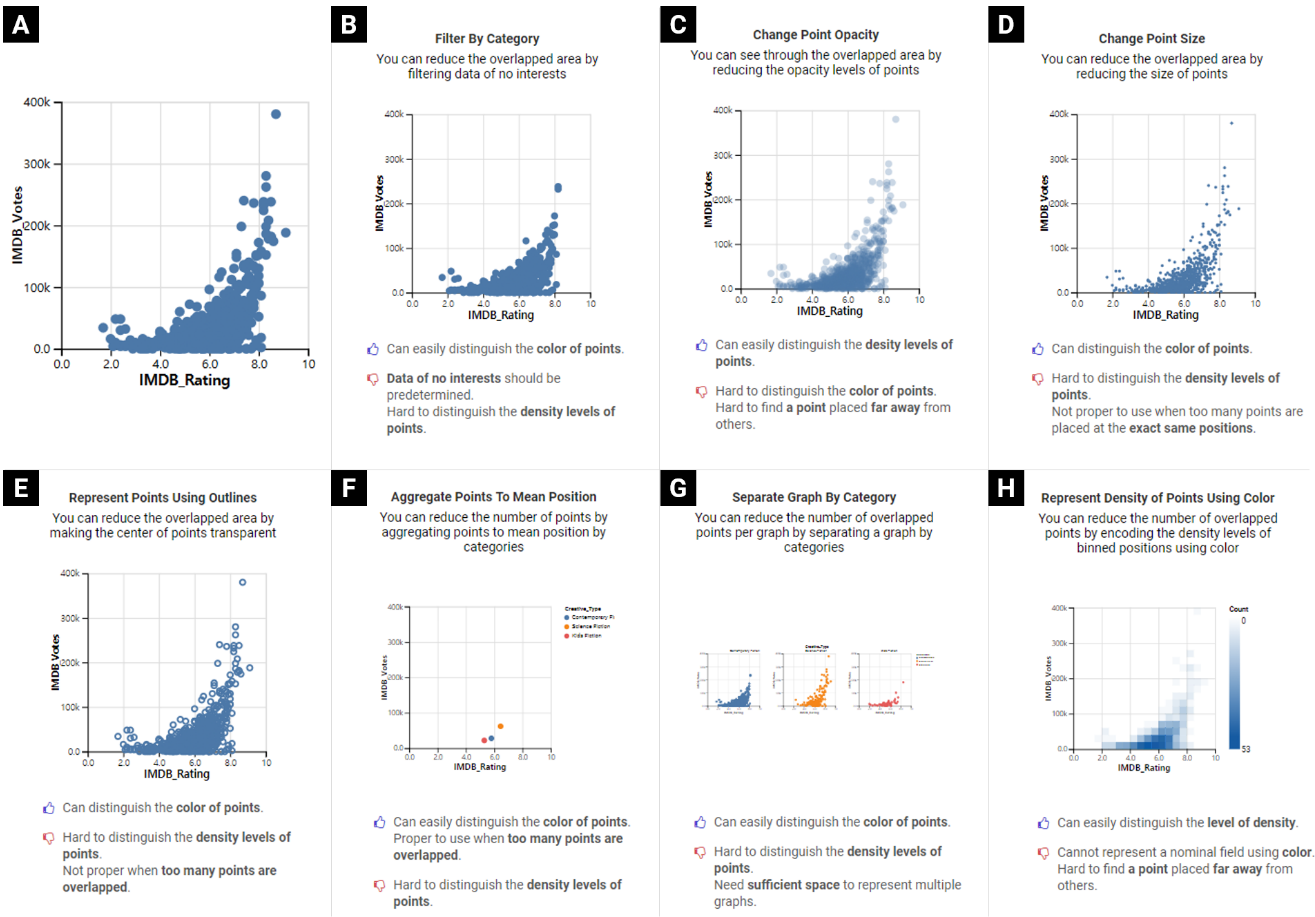

Figure 1: *The seven recommendations (B-H) in our interface for alleviating over-plotting problems in the (A) specified scatterplots.*

Category: remove points of no interests; (C) *Change Point Opacity*: change the level of opacity to see through overlapped area; (D) *Change Point Size*: re-size points to reduce the overlapped area; (E) *Represent Points Using Outlines*: remove fill color of points to reduce the overlapped area; (F) *Aggregate Points To Mean Position*: show mean values of each category to reduce the number of points in the display; (G) *Separate Graph By Category*: divide graphs to reduce the number of points per scatterplot; and (H) *Represent Density of Points Using Color*: show density by binned area rather than displaying individual points.

3.3. Representation Methods for Recommendations

By reviewing studies related to recommendation systems [WQM*17] and InfoVis novices [HR07, GTS10, RM15], we designed three representation methods to describe each of the seven recommendations to support novices in understanding recommendations and their usefulness.

3.3.1. Preview

Preview, the most widely used method to represent visualization recommendations in existing tools [WMA*16, WQM*17, Exc18, MHS07, WW10, VRM*15, vdEvW13, BGV16, GW09, KHPA12, SKC*11, DW14, EB11] (Figure 2A), shows the visualization result where the suggested visual mapping is applied over the current visualization. By showing the suggested visualization result in advance, users might easily presume and compare the usefulness of recommendations as illustrated by Grammel et al. [GTS10]. Between two types of previews, we used actual visualization results rather than thumbnails because our recommendations are data- or encoding-level suggestions, which require detailed representations.

3.3.2. Animated Transition

While Preview shows the result visualization as a static image, Animated Transition (Figure 2B) connects the gap between the current visualization and Preview by showing smooth transitions. According to previous work [HR07, RM15], animated transitions allowed novices to better understand new visual mappings. Since InfoVis novices often confront *visual mapping* and *interpretation barri-*

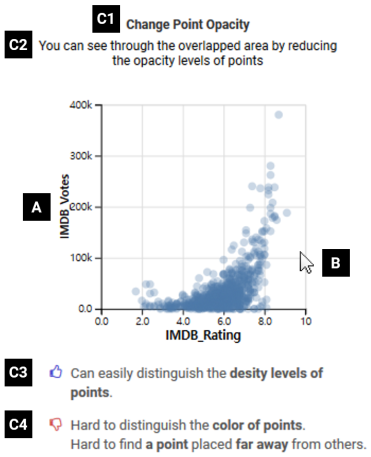

Figure 2: *Three representation methods for a visualization recommendation: (A) Preview, (B) Animated Transition on mouse hover, and (C1-4) Textual Description.*

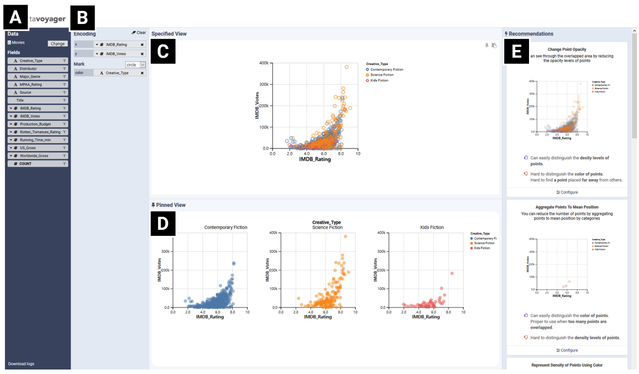

Figure 3: *Overall interface of the modified PoleStar [WQM*17] with the recommendation interface: (A) data panel, (B) encoding panel, (C) specified view, (D) pinned view, and (E) recommendation interface.*

ers [GTS10] in the visualization construction process, Animated Transition might further help users understand the behavior of new visual mappings in recommendations.

For the relatively large difference between the current visualization and Preview (i.e., *Aggregate Points To Mean Position* in Figure 1F), we used a staged transition [HR07] to help users follow the changes: points are first colored by a default nominal field and then moved to mean positions of their categories.

3.3.3. Textual Description

According to Grammel et al. [GTS10], providing explanations about recommendations is important to give deeper insight. Such explanations include *what* the recommendation is about, as in [WQM*17]; *why* it is important; and what *advantages* and *disadvantages* there are. We generated the four types of descriptions in our interface (Figure 2C1-4). For the advantages and disadvantages, we generated descriptions based on four major criteria referring to a clutter reduction taxonomy [ED07]: *can show point color*, *can show overlap density*, *can show outlier*, and *is scalable to large data*.

Because the readability of textual descriptions would affect InfoVis novices' ability to understand them, we constructed and revised the textual descriptions with care to make them readable to novices. We extracted explanations about each recommendation in the literature [ED07, Few09] and then conducted a two hour discussion session with an InfoVis novice to create novice-friendly expressions. During this in-person interview, we reviewed four types of textual descriptions (i.e., *what*, *why*, *advantages*, and *disadvantages*) of seven recommendations sentence by sentence. The text we created was targeted to *users* rather than *designers* because we assumed that novices are more likely to view themselves as users; for example, we used "*Can **see** point color*" rather than "*Can **show** point color.*" In addition, we clarified ambiguous expressions (e.g., "*Not scalable to **large data***" had been changed to "*Not appropriate when **too many points overlap***"). We then assessed the readability of the text descriptions in a pilot study (section 3.5) before the main study.

3.4. Interface

We implemented our recommendation interface on PoleStar [WQM*17], an open-source visualization tool that allows users to construct visualizations based on a Cartesian coordinate system. The main reason for using the system is that it uses a shelf-configuration interface [GBTS13], which is one of the most widely used interfaces in existing tools such as Tableau [Tab18], Polaris [STH02], and PivotTable in Microsoft Excel [Exc18]. By using the familiar interface, we expected users might easily learn about the tool within a short training session. As we focused on constructing scatterplots, we modified PoleStar to support only scatterplots. Moreover, to encourage participants actively use recommendations, some visual encoding features in the modified PoleStar, such as separating graphs or filtering, were hidden from PoleStar and supported only in the recommendation panels.

The overall interface of modified PoleStar with the recommendation interface is shown in Figure 3. The data panel shows a list of data fields (Figure 3A), and users can connect the fields to visual properties (e.g., x/y axis or color) in the encoding panel (Figure 3B). The specified view in the middle (Figure 3C) shows the visualization that is defined in the encoding panel. To facilitate comparison of the visualizations users construct, we enabled users to pin their visualizations to the bottom of the window (Figure 3D) by clicking on the Pin button.

The recommendation panel in the right-most area (Figure 3E) shows the seven recommendations in a gallery-style layout [GTS10] for easy comparison between alternatives. In each recommendation, Preview and Textual Description are shown as static representations, while Animated Transition is displayed upon mouse hover on Preview. Users can apply the suggested visual mappings to the specified view after they adjust parameters (e.g.,

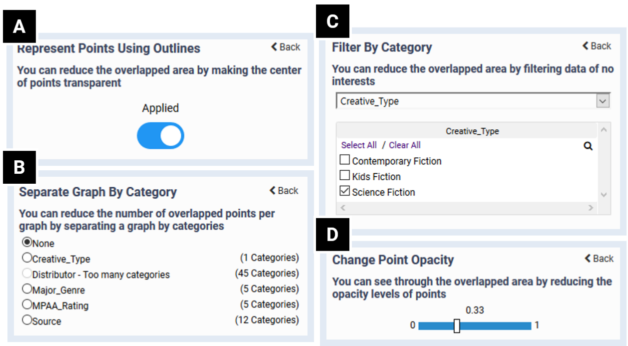

Figure 4: *Configuration interfaces for recommendations: (A) toggle button for Represent Points Using Outlines and Represent Density of Points Using Color, (B) nominal field picker for Aggregate Points To Mean Position and Separate Graph By Category, (C) category picker for Filter By Category, and (D) slider bar for Change Point Size and Change Point Opacity.*

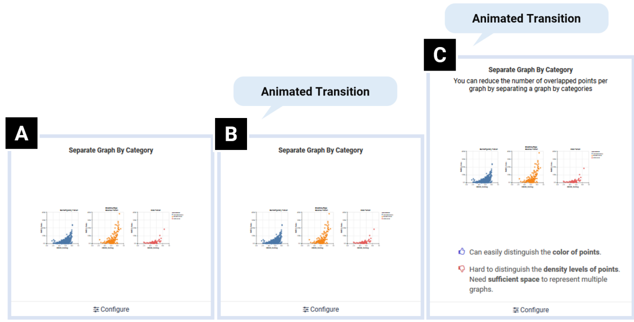

Figure 5: *Three combinations of representation methods used in our study: (A) Preview + Title (PT), (B) PT + Animated Transition (PTA), and (C) PTA + remaining Textual Description (PTAT).*

change the level of opacity for *Change Point Opacity* or select a data field and categories for *Filter By Category*, Figure 4C-D). For the recommendations that do not support adjustable parameters (e.g., *Represent Density of Points Using Color*), the interface shows simple toggle buttons to apply recommended visual mappings over the specified view (Figure 4A).

3.5. Pilot Study

We conducted a pilot study with six participants to evaluate the feasibility of the recommendation interface and the study design. The participants used the interface for about half an hour to solve six questions related to major scatterplot tasks [SG18]. After the pilot study, we improved the interface based on the participants' feedback. Firstly, we highlighted keywords in the Textual Description using font weight to improve readability (e.g., "Can see **point color**"); we did not use other highlighting methods with better pop-out effects such as a yellow background or larger font [RM15] because we assumed that such methods would distract users during the visualization construction process. Secondly, we changed the trigger method for Animated Transition. We initially had placed a Play button for the transition in each recommendation so that users could see the transition on demand. However, users occasionally forgot about the existence of Animated Transition during cognitively challenging tasks in the study. As we wanted to see the effects of Animated Transition during the study, we instead chose to display animated transitions when users hover the mouse over Preview. Thirdly, we empirically chose the duration of the animated transition considering participants' feedback: one second long for each staged transition, consistent with previous design guidelines (e.g., [RCCR02]). Finally, Animated Transition was initially positioned on top of the specified view, but moved to the recommendation panel because some participants commented that it being placed far from Preview and Textual Descriptions somewhat confused them.

4. User Study

To better understand how InfoVis novices use visualization recommendations during a visualization construction process, we conducted a qualitative study on our recommendation prototype using a think-aloud protocol.

4.1. Participants

We recruited 24 participants (10 female), ages 18 to 33 years, from a university. They were self-reported to use visualization tools 4.2 times per month on average. The most frequently used visualization tool was Microsoft Excel [Exc18] (21 participants), while a few participants also used R [R18], Origin [Ori18], MATLAB [MAT18], and Tableau [Tab18]. Most participants (21 participants) reported to have no prior knowledge about information visualization; only three participants were aware of InfoVis from lectures related to statistics tools (e.g., R or MATLAB) at university or at work. Participants received about $10 for their participation.

4.2. Interface

Participants used one of three combinations of representation methods in our qualitative user study. Three combinations of representations were designed to provide different levels of information about recommendations: 1) Preview + Title (PT, Figure 5A), 2) PT + Animated Transition (PTA, Figure 5B), and 3) PTA + remaining Textual Description (PTAT, Figure 5C). The main reason for providing Title (i.e., Textual Description about *what*) for all conditions was that most of the encoding-level recommendations (e.g., [WQM*17, WMA*16]) use previews with simple titles, possibly because novices are unlikely to fully understand the small difference between the specified view and Preview.

The layout of the modified PoleStar was fixed across all participants, and the width of recommendation panels was 410 px. We limited the space of the recommendation panels to reflect common recommendation interfaces that show only a few recommendations at once, making users interact with scroll views (e.g., [WMA*16, WQM*17, KHPA12]). In the study layout, only two recommendations were visible for the PTAT condition (all methods

Table 1: *Six questions based on scatterplot-related visualization tasks [SG18] used in our study.*

ID	Questions
Q1	Is there a correlation between **US_Gross** and **Worldwide_Gross**?
Q2	Draw a scatterplot that shows a relationship between **IMDB_Score** and **IMDB_Votes**. In which area is movies most densely placed?
Q3	Find a point far away from others in a scatterplot that shows a relationship between **Production_Budget** and **Worldwide_Gross**.
Q4	Which **Genre** has the highest **Production_Budget** and **Running_Time** on average?
Q5	Of movies whose **Distributor** is either *Paramount Pictures* or *Sony Pictures*, what are the ranges of **Production_Budget** and **Worldwide_Gross**?
Q6	Of movies whose **IMDB_Scores** and **Rotten_Tomatoes_Scores** are higher than *6* and *60*, what is the most common **Creative_Type**?

together), while other conditions showed an additional recommendation (i.e., three recommendations). We randomly ordered seven recommendations across all participants to prevent order effects.

4.3. Tasks and Datasets

We designed six questions (Table 1) based on scatterplot-related visualization tasks [SG18], which are constructed by surveying scatterplot-specific analysis scenarios in InfoVis literature, and are frequently employed in controlled user studies as study tasks (e.g., [KH18, CEJ*18]). Each question was designed to reflect either a browsing-related task or an aggregate-level task [SG18] (i.e., Q1 and Q6 are browsing-related tasks while Q2-Q5 are aggregated-level tasks). We had not considered object-centric tasks because they are less related to over-plotting problems.

When visualizing the prepared dataset with scatterplots, over-plotting problems made it difficult to answer to four of the questions (all questions except Q1 and Q3) without alleviating the problems. Therefore, participants had to use the recommendation interface to answer the questions.

For a training session, we prepared a SAT score dataset that consisted of scores and grades of 143 students in five subjects and some demographic data (i.e., gender, region, education level). For the main task, we used a movie dataset [WMA*16] that contained classifications of 746 movies (e.g., genre, creative type, MPAA rating, and distributor) and their budgets, worldwide/US gross, play times, review scores and the number of votes.

4.4. Procedure

After signing a consent form and completing a pre-study questionnaire, participants were introduced to the overall procedure and the task for about five minutes. Because the focus of our study is to explore how participants understand and use unfamiliar recommendations instead of unfamiliar visualizations themselves, participants were also introduced to a scatterplot visualization to make them get familiar with it. They then had a training session during which they were introduced to the interface and practiced constructing scatterplots using the interface to answer six practice questions based on the SAT score dataset. The participants had to understand about the seven recommendations only with the given interface; the experimenter did not explain any about the recommendations. By answering to the practice questions, the participants became familiar with their tasks. After the training session, participants were asked to complete the main task in which they used the interface to construct scatterplots based on the movies dataset [WMA*16] to answer six questions (Table 1). Participants were asked to construct scatterplots that clearly show the answers to the questions by using the recommendation panel. After they constructed each scatterplot, they pinned the scatterplot, answered to the question, and moved on to the next question. Participants repeated this process until they answered the last question. We recorded the screen during the practice and main tasks. Upon answering all the questions, they were asked to complete a questionnaire that included an assessment of how much (7-point scale) each representation was helpful for understanding the recommendations and the reasons for thinking that each of them is useful or not (e.g., participants in the PTAT condition assessed all three representation methods). Then, we asked participants to think aloud about their visualization construction process by watching the recorded video before conducting an open ended interview. Participants were allowed to rest at any time during the study. The entire study procedure took about 45 minutes on average per participant.

5. Findings

Participants produced diverse scatterplot designs using different recommendations, more than four different designs per question (Figure 6). Of 144 scatterplots (24 participants x 6 questions), 35 scatterplots were constructed without using any recommendations, mostly for Q1 and Q3; 89 scatterplots were generated using only one recommendation; and the rest (20 scatterplots) were constructed using two or more recommendations together. In all cases, recommendations were used to alleviate the over-plotting problems in the scatterplots, except one participant (P12_{PTAT}) who used *Change Point Size* to make the outlier more visually salient by increasing the size (Figure 6 Q3-*Outline+Size* and Q5-*Filter+Size*).

5.1. Poor Design Decisions

Of 144 answers to the questions, two of them were incorrect: P13_{PT} reported to have read the category name incorrectly in the color legend (Figure 6 Q4-*Aggregate*), and P20_{PTAT} did not use *Filter By Category* because she did not understand it well, making it difficult for her to answer Question 5 (Figure 6 Q5-*None*). We fur-

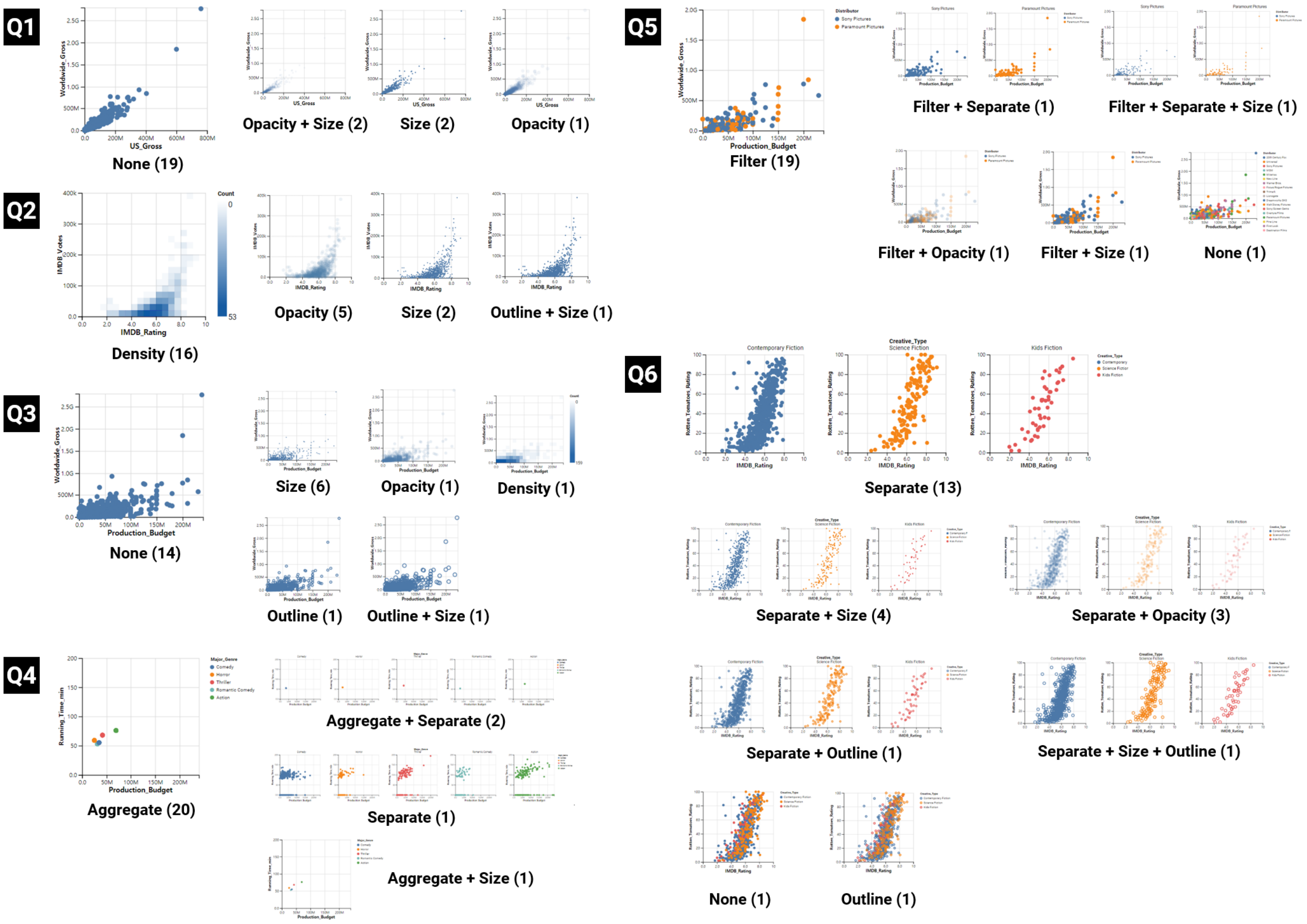

Figure 6: *Scatterplots constructed by the participants in our study in response to Question 1 to 6. Each scatterplot is labelled with the name of recommendations which are used to make the visualization. Recommendation names are abbreviated: 1)* ***Filter*** *By Category, 2) Change Point* ***Opacity****, 3) Change Point* ***Size****, 4) Represent Points Using* ***Outlines****, 5)* ***Aggregate*** *Points To Mean Position, 6)* ***Separate*** *Graph By Category, and 7) Represent* ***Density*** *of Points Using Color. The number in parentheses represents the number of participants who constructed the visualizations.*

ther discuss such challenges for understanding recommendations in subsection 5.3. Although the rest of the scatterplot designs derived correct answers, we identified several poor design decisions. For example, the goal of Question 3 was to clearly show the outlier in the scatterplots, but some participants (8 of 24 participants) either reduced the size or opacity of points or used density plots, which unintentionally led to making the outlier hard to notice (Figure 6 Q3-*Change Point Opacity*, Q3-*Change Point Size*, and Q3-*Represent Density of Points Using Color*). Three participants made similar poor decisions in Q5 (i.e., Figure 6 Q5-*Filter+Opacity* and Q5-*Filter+Separate+Size*). Of all 10 participants (8 for Q3 and 2 for Q5), only one used the PTAT condition, possibly because the Textual Description about advantages and disadvantages contained explanations about the outlier (e.g., "*Hard to find a point placed far away from others*" in *Change Point Opacity*).

5.2. Role of Preview, Animated Transition, and Text

The most common representation method–Preview–was reported to be most useful when understanding and selecting recommendations (5.9 out of 7) and identified as the most intuitive: *"I was able to understand recommendations at a glance by Preview"* ($P5_{PTA}$). On the contrary, Animated Transition was less helpful than Preview on average (3.9 out of 7) but still useful for understanding recommendations when the difference between the specific view and Preview is relatively large (e.g., *Aggregate Points To Mean Position* and *Separate Graph By Category*): *"[Animated Transition] was not essential but helpful when understanding large changes."* ($P18_{PTA}$). Although Preview was the most intuitive representation for most participants, a few (12.5%) said that they preferred textual descriptions. One said that *"[advantages and disadvantages] give insight about recommendations."* ($P17_{PTAT}$). This is consistent with the study result: participants who read advantages and disadvantages (i.e., PTAT condition) barely used *Change Point Opacity*, *Change Point Size*, or *Represent Density of Points Using Color* when they had to make the outlier noticeable in Q2 and Q5. Some participants provided other reasons for preferring Textual Description: they found it hard to compare differences between previews. We might interpret this tendency by *interpretation barrier* [GTS10], where novices are likely to confront difficulties in interpreting visualizations. Because of the barrier, some participants seemed to intensively rely on Textual Description. For example, to solve Question 2, some reported that they used density plots rather than *Change Point Opacity* simply because the title or the advantage description contained *"density."* This seems to be the one of the main reasons why *Represent Density of Points Using Color* was used much more than *Change Point Opacity*, as illustrated in Figure 6 Q2 (i.e., 16 times for the density plots and five for the other).

Although participants preferred a specific representation of the three methods, most reported to have used multiple methods together, as they expected and confirmed the behavior of suggested visual mappings to more clearly understand them. For example, they saw a preview and then expected the behavior of the recommendation. Whenever they had not clearly understood about the recommendation, they saw textual descriptions or animated transitions to confirm their hypothesis.

5.3. Challenges For Understanding Recommendations

The biggest challenges participants confronted in understanding recommendations was identifying the difference between pairs of visualizations. This includes distinguishing 1) **between the specified view and Preview** and 2) **between recommendations themselves**. For example, $P20_{PTAT}$ did not use *Filter By Category* in the study. During the interview, he said he had not clearly understood the recommendation because the difference between the specified view and Preview was subtle (Figure 1A and B). He had not tried to understand the recommendation clearly, and this led to never using it. Similarly, $P12_{PTAT}$ reported that whenever the previews were not distinguishable, he did not use them. Animated Transition seemed not to show the difference clearly as $P20_{PTAT}$ said, *"Fun to see, but the [visual change] of Animated Transition was subtle."*

Distinguishing between recommendations themselves also includes **comparing textual descriptions**. $P6_{PTAT}$ and $P12_{PTAT}$, for example, said they mistakenly thought that *Filter By Category* and *Separate Graph By Category* are the same because they contained the same keyword (i.e., *category*, Figure 1B and G). Moreover, $P6_{PTAT}$ and $P20_{PTAT}$ said it was hard to compare the descriptions of advantages and disadvantages between recommendations because some sentences are redundantly placed across a few recommendations (e.g., "Can easily distinguish the **density** levels of points", Figure 1C and H).

5.4. Learning By Doing

Six participants reported that playing with configurable parameters of recommendations (e.g., re-sizing points by a slider bar in Figure 4) in addition to using the three representation methods helped them understand the recommendations (i.e., *learning-by-doing* [KL16]). For example, $P10_{PTAT}$ said he better understand *Change Point Opacity* when he adjusted the level of opacity using the slider bar (Figure 4D): *"[The] difference [between the specified view and Preview for Change Point Opacity] was subtle, but I understood [Change Point Opacity] by adjusting it."* Similarly, the behavior of *Filter By Category* was not initially clear to some participants because the changes between the specified view and Preview was subtle for them. However, they reported that once they adjusted and applied the recommendation, they clearly understood what it does: *"Once I configure [...], I understand it clearly"* ($P21_{PT}$).

5.5. Effects of Recommendation Order

Figure 7 shows the number of times participants chose recommendations by their order during the task. Note that the seven recommendations were randomly ordered for each participant. As can intuitively be expected, the last one was least frequently selected: "*I haven't seen the density plot (the last one) when using the system*" ($P11_{PTA}$). The reason for such a trend seems to be that the participants regarded the later ones as less important; as $P9_{PTAT}$ said, "*I felt that recommendations on the bottom are less effective than first few ones. So perhaps I skipped using the last one.*" Interestingly, the number of times participants selected recommendations in the middle (i.e., 4th and 5th) dropped to some degree. $P12_{PTAT}$ gave a possible reason for this tendency: *"I think I occasionally skipped recommendations on the middle. Perhaps it is because previews looked similar to each other to me when scrolling down."* According to the feedback, making the differences more visually salient might address the problem of missing recommendations in the middle while scrolling down.

5.6. Personal Criteria for Selecting Recommendations

We were also interested in the criteria that participants have in their mind when selecting recommendations. Knowing the users' diverse criteria, designers might consider users' needs when designing recommendation systems. Because their task was constructing visualizations that best illustrate answers to the questions, all participants tried to select recommendations that make the visualization perceptually better. However, they still had options to chose between recommendations that provide similar information (e.g., density plot or *Change Point Opacity* to see the density of the overlapped area). The most frequent criterion was an aesthetic perspec-

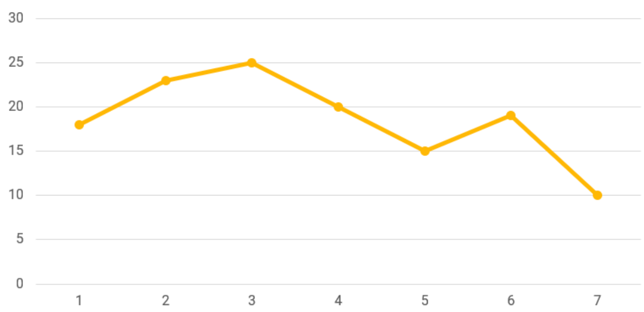

Figure 7: *The number of times recommendations were chosen by their order during the task.*

tive (35.5% participants) followed by familiarity (12.5%). Two participants used recommendations that were more familiar to them, while one participant wanted to use unfamiliar recommendations on purpose: *"I tried to use recommendations which I have never used before like [density plots]. I wanted to learn new visualizations"* (P15$_{PTA}$). Another participant said he used recommendations that support adjustable parameters: he used *Change Point Opacity* rather than *Represent Points Using Outlines* because the former supports changing the level of opacity, while the latter did not support such an adjustable parameter.

6. Discussion

6.1. Design Implications

Based on our findings, we propose three implications for improving the design of recommendation interfaces in visualization tools.

6.1.1. Highlight Subtle Differences

When providing recommendations, each recommendation should be distinguishable from the others in terms of graphical previews and textual descriptions (e.g., titles), and each recommendation should also be distinguishable from the specified view. When differences are subtle, novices might have a hard time understanding the behaviors of the recommendations or might miss some of them while using the recommendation interfaces. One method to avoid subtle differences might be making the difference clearer to novices using additional visualization techniques. Using the animated transition could be one option, but in our study, some participants still found it hard to see the visual changes in transitions when the differences are relatively small (e.g., *Represent Points By Outline*). We used one second for each staged transition, consistent with previous design guidelines (e.g., [RCCR02]), but designers should consider increasing the duration to make animated transitions more noticeable. Moreover, several other techniques would be useful to further make the changes clearer, such as emphasizing the differences using annotation methods (e.g., [RBL*17]) or extending visualization techniques for visual comparison [GAW*11] to recommendation interfaces. If additional techniques cannot be used, aggregating recommendations by their visual similarities would be another possible method (e.g., clustering recommendations as in [WQM*17]).

6.1.2. Use Multiple Representations Together

Recommendation interfaces should combine multiple representations to support the novices' *expect-and-confirm* process. Since novices often experience *interpretation barriers* [GTS10], a single representation would not be enough for them to clearly understand the recommendations. In such situations, seeing another representation helped users more clearly understand unfamiliar recommendations. For example, in MS Excel 2016 [Exc18], recommended visualizations are provided with thumbnail previews. However, users might find it hard to distinguish between recommendations such as between Stacked Bar and 100% Stacked Bar only with the preview. Our findings suggest that recommendation interfaces should at least provide previews with clear titles unless rendering actual chart is not feasible within given resources. Although previews are the most intuitive representations, novices still prefer textual descriptions because novices sometimes do not feel confident about what they have understood by previews.

6.1.3. Support Learning By Doing

The learning-by-doing approach [KL16], which is known to be useful for learning parallel coordinate plots, was also useful for understanding the behavior of recommendations during the visual construction process. Therefore, we believe visualization recommendation interfaces must support the learning-by-doing approach by giving users the opportunity to play with recommendations. In our recommendation interface, we showed adjustable interfaces (e.g., a slider bar) after users pressed a button. Possibly because of this, one participant misunderstood a recommendation and had no chance to try it. Hence, it might be more effective to make adjustable interfaces visible to users together with other representation methods (e.g., Preview), regarding the adjustable interface as one of the representation methods for describing recommendations.

6.2. Limitations and Future Work

Our controlled user study had several limitations in terms of external validity. First, we limited the users' visualization tasks to scatterplot clutter reductions to make the study analysis more efficient. To extend our findings to a more general visualization construction process, it would be necessary to explore representation methods with different visualizations and tasks. Second, our study prototype provided a limited number of recommendations. However, the number of recommendations can become larger in the real-world, which complicates the generation process of textual descriptions. In our study, we manually constructed the textual descriptions with care because the readability can disturb novices in the cognitively challenging tasks of the visualization construction process. State-of-the-art natural language generation (NLG) techniques (e.g., [FVL*07]) might help generate the descriptions in a more efficient manner, but the readability should be carefully assessed. Constructing NLG models for textual descriptions in recommendations would be a promising research direction.

We believe evaluating recommendation forms in terms of task time and accuracy is equally promising research direction. In our study, we did not evaluate them in terms of the quantitative aspects because we wanted to let the participants use recommendations for enough time during the visualization construction tasks. We thought if participants construct visualizations with the time pressure, they might end up using only first few recommendations without sufficiently thinking about their visual encodings or ignoring to use some of representations (e.g., textual descriptions or animated transition), which are the cases we tried to prevent for understanding the usage of each representation/recommendation. We leave the quantitative evaluation as a separate future study.

In the future, it would also be interesting to design and evaluate visualization techniques for emphasizing subtle differences between visualizations or illustrating the causality of visual changes. Analyzing novices' behaviors related to recommendation systems based on gaze patterns would be equally promising to explore. Additionally, it would be also interesting to determine the effect of other combinations of representation methods, such as using only textual descriptions or preview without animated transitions, or even additional representation methods we had not used.

7. Conclusion

We performed a qualitative user study to broaden the understanding of the behavior of InfoVis novices when using recommendation systems to perform scatterplot clutter reduction tasks. We designed a recommendation interface using three primary representation methods (i.e., Preview, Animated Transition, and Textual Description) and found that different representations individually and cooperatively help users understand and choose recommended visualizations. Based on the study results, we presented three design implications for designing more efficient visualization recommendation interfaces for InfoVis novices.

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