

Bottom-up vs. Top-down: Trade-offs in Efficiency, Understanding, Freedom and Creativity with InfoVis Tools

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ABSTRACT

The emergence of tools that support fast-and-easy visualization creation by non-experts has made the benefits of InfoVis widely accessible. Key features of these tools include attribute-level operations, automated mappings, and visualization templates. However, these features shield people from lower-level visualization design steps, such as the specific mapping of data points to visuals. In contrast, recent research promotes constructive visualization where individual data units and visuals are directly manipulated. We present a qualitative study comparing people’s visualization processes using two visualization tools: one promoting a top-down approach to visualization construction (Tableau Desktop) and one implementing a bottom-up constructive visualization approach (iVoLVER). Our results show how the two approaches influence: 1) the visualization process, 2) decisions on the visualization design, 3) the feeling of control and authorship, and 4) the willingness to explore alternative designs. We discuss the complex trade-offs between the two approaches and outline considerations for designing better visualization tools.

Author Keywords

Information Visualization; Tableau Desktop; iVoLVER.

ACM Classification Keywords

H.5.m Information Interfaces and Presentation (e.g. HCI): Miscellaneous; D.1.7 Software: Visual Programming

INTRODUCTION

Visualization tools for non-experts—people with no formal training on visualization concepts—are increasingly popular, and allow millions to create their own visual data representations for a multitude of purposes. However, to create effective visualizations people still need to learn the principles of visualization design (e.g., what data types should be mapped to which visual attributes).

The gateway to this knowledge is usually the same digital tool that is used to create the visualization. People will therefore learn as they experiment with an interface which might not have been designed for supporting an understanding of effective visualization design. To better support non-experts vis

designers to leverage the power of visualization it is important to understand how they go about creating visualizations and how the tools themselves affect this process.

We explore these questions by comparing the use of Tableau Desktop, a heavily automated visualization tool, with iVoLVER, a digital tool based on the philosophy of constructive visualization as proposed by Huron et al. [24]. We present a qualitative study investigating how these tools influence non-experts’ approaches to the visualization process, the differences in the resulting visualizations, design choices, low-level visual mappings, and justifications of these approaches. Our findings show trade-offs between these visualization construction approaches. In our study, Tableau enabled the speedy exploration of visualization solutions with minimum input from the user, yet it did not promote a critical understanding and reflection on the visualization process and outcomes. As a constructive tool iVoLVER required initial thinking about the intended visualizations and a hands-on, sometimes tedious procedure of mapping data to visuals. This resulted, however, in a transparent, flexible visualization process facilitating creative and critical thinking as well as a feeling of control and authorship.

With our study results we contribute: 1) a characterization of non-expert visualization processes comparing two tools with different approaches to visualization construction; 2) a discussion of how these tools’ paradigms influence non-expert’s visualization design decisions; and 3) a reflection on the complex set of trade-offs we found between the two studied approaches. Our findings provide guidance on designing tools that support the development of visualizations as well as learning the principles of visualization design.

RELATED WORK

Three research areas are relevant to our study: the fundamentals of the InfoVis design process, existing vis tools, and empirical studies on visualization construction.

The Visualization Design Process

Several authors have discussed the different stages and key elements of visualization design (e.g., [5, 11, 15, 36, 39]). Card et al. [10] describe the process of creating visual data representations as a set of four steps: 1) data analysis, 2) filtering, 3) mapping, and 4) rendering. Step 3—the creation of mappings between visual properties and data attributes—is one of the most important and well researched elements of visualization design. Much of the InfoVis research of the last 50 years focuses on the perceptual properties of visual elements [13] and the fit between the data types and the marks

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CHI 2017, May 06 - 11, 2017, Denver, CO, USA.

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ACM 978-1-4503-4655-9/17/05 \$15.00

DOI: <http://dx.doi.org/10.1145/3025453.3025942>

and visual properties to represent them (e.g., [3, 4, 32, 43]). We are interested in representational mapping as an important part of the process. In particular, our focus is on the types of mappings that people come up with when designing their own visualizations. This relates to recent research on how people sketch data representations. Walny et al. [42] describe a “representation continuum” that shows a wide range of levels of abstraction when people sketch up representations of small datasets by hand, from *countable* (concrete and numeric) to *pictorial* (abstract) representations.

Visualization Tool Types

Visualizations are typically built using digital tools, and a large variety of these tools exists [9, 17, 33]. Many tools allow to produce similar outcomes with different interfaces. Based on Grammel et al.’s categorization [17], three types are most relevant to our work: template editors, shelf configuration tools, and visual dataflow programming tools.

According to Grammel et al., in *template editors* “the user selects some data and then picks a pre-defined visual structure in which to represent it. The distinguishing criteria of this approach are the separation between the initial visualization selection steps and the refinement of the selected visualization” [17]. A related concept is “using tools” as described by Victor [40]. Examples of template tools are Many Eyes [41] and MS Excel. Tableau Desktop’s “Show me” pane is a template feature within what is mostly a shelf configuration tool.

Shelf configuration tools allow the specification of mappings through simple GUI operations on collections of visual properties and data attributes that are presented visually. Customization—typically based on cursor operations (e.g., drag-and-drop) or menus and dialogs—requires additional steps. Tableau Desktop and Lyra [37] (a more recent research prototype) fall within this category.

Visual Dataflow Programming tools enable designers to specify visualizations by connecting elements (nodes) through links. The graph of connected components defines the dataflow and the characteristics of the visualization. This approach has a long history (e.g., [1, 29]) but is also present in more recent tools such as ExPlates [27], DataMeadow [16], and iVoLVER [31].

Besides Grammel et al.’s categorization [17] of visualization tools we can also distinguish between more high-level approaches to vis construction: bottom-up and top-down.

In a **bottom-up** approach one starts at a low level of abstraction, by manipulating individual data points and attributes to incrementally generate the overall visualization. Related to bottom-up approaches is the idea of *constructive visualization*, which Huron et al. define as “the act of constructing a visualization by assembling blocks, that have previously been assigned a data unit through a mapping.” [23, pp. 436]. Constructive visualization is grounded in educational theories such as Papert’s Constructionism [34] and Piaget’s constructivism [2, 35]. Because of their educational roots, constructive tools might be more accessible to non-experts [24, 25] and appropriate for teaching visualization. Visualization tools implementing constructive principles can be considered bottom-up. We consider iVoLVER an example of both.

In contrast to tools applying a bottom-up approach, in **top-down** tools decisions about the visual representation of data happen at an attribute level. Template-based and shelf configuration tools inherently follow this approach—they focus on the overall mapping between attributes and visuals first. Customizations can be applied only after the initial attribute-level mappings are created. Data mappings performed in this way typically include all data points of an attribute, or even the entire dataset. The manipulation of the visual representation at an individual data point level is generally not possible (e.g., in Tableau visual mapping actions include all data points associated to a single attribute).

The tool categories and approaches to vis construction can potentially lead to different outcomes and design processes—a relevant issue for designers of visualization authoring tools.

Previous Empirical Findings

Grammel et al. [18] studied how novices indirectly designed visualizations by instructing a Tableau expert to create the visualizations according to their specifications. Although participants did not directly use Tableau, the study findings are valuable and relevant, since data attribute selection, template selection, and visual mapping were identified as the main activities of the process. The study also showed that participants often missed relevant steps and specifications (e.g., specific mappings) when communicating with the expert.

Wun et al. [44] compared building bar charts using MS Excel vs. a set of physical tiles. They found that the building process was very different for the two tools. Our research complements and expands theirs in that we compare two digital tools (eliminating the possible physicality confound), and we do not restrict the visualization designs to bar charts.

TWO VISUALIZATION TOOLS

To investigate the virtues and problems of bottom-up and top-down approaches to visualization design, we chose two tools that represent two ends of this continuum. This section discusses the two tools and their differences.

On the top-down end of the continuum we have traditional shelf configuration and template-based tools (as defined in [17, 40]). Tableau Desktop¹, a current leader in the visualization tool market, is a shelf configuration tool and therefore a representative of the top-down approach. Tableau’s main interface is divided into rectangular panes. Once the data is loaded the user can see a pane containing the different data attributes (A in Fig. 1). Dragging and dropping attributes from this data pane onto the columns and rows shelves (B in Fig. 1) triggers a separate visualization pane (C in Fig. 1) to display a default data representation that is automatically selected by the system according to the selected attributes. An additional pane enables adjustments of the marks’ visual properties by dropping data attributes to other shelves of the interface (D in Fig. 1). A further pane, “Show-me” (E in Fig. 1), provides a gallery with several visualization templates (e.g., choropleth map, area charts). The templates that are not available with the current attribute selection are automatically grayed out.

On the opposite end of the spectrum we have tools that support a bottom-up approach to visualization construction

¹<http://www.tableau.com>

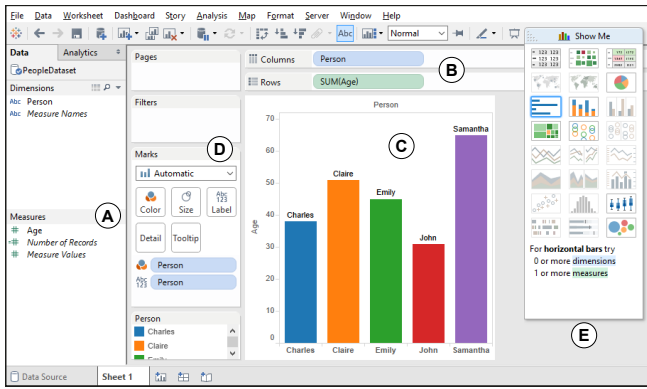


Figure 1. Tableau Desktop Interface.

such as those implementing *constructive visualization* principles [22, 23, 24, 25]. In bottom-up tools people explicitly establish mappings between individual data points and the graphical elements that represent them. The final visualization emerges as the result of many small-scale decisions and manipulations. As representative of this approach we selected iVoLVER [31], the **I**nteractive **V**isual **L**anguage for **V**isualization **E**xtraction and **R**econstruction, because it is digital as Tableau Desktop and the code is recent, open, and available on-line.² iVoLVER is based on an infinite zoomable canvas interface. On opening the tool the user imports the data which appears directly on the canvas (e.g., a table of data will be composed by numbers and lines that are canvas objects; see A in Fig. 2). In addition to the data there are other objects such as marks or positioner widgets, that can be dragged from a palette (B in Fig. 2) into any position on the canvas and subsequently be linked to the data or to each other. A toolbar on top provides access to global options such as selecting the data to import or showing or hiding the connections between canvas objects (C in Fig. 2).

Tableau Desktop and iVoLVER are both digital tools and share the use of marks (as defined by Bertin [4]) and visual properties [12, 13] as central concepts in visualization design. Additionally, neither of the tools requires textual programming and both support dragging and dropping interactions; however, the two fundamentally differ in their underlying design approach, which results in important differences that motivate our study, as discussed below.

²<http://ivolver.cs.st-andrews.ac.uk>

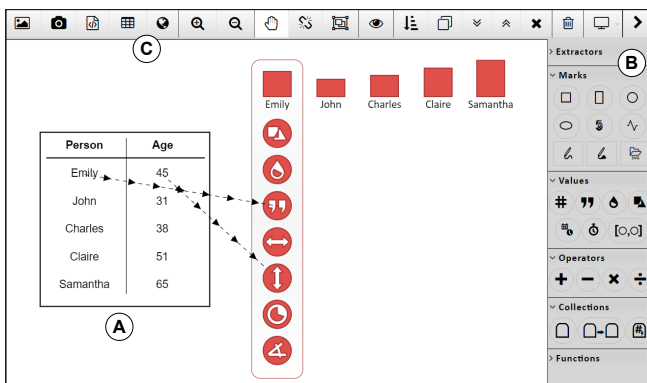


Figure 2. iVoLVER Interface.

Data Granularity and Operation Repetition

The main activity of designing visualizations in Tableau Desktop consists of the assignment (through drag-and-drop), of a data attribute to a visual dimension (row or column) or a visual property. A key point here is that Tableau users do not have the option to manipulate individual data points, but instead deal with the full range of data by attribute. Interactions happen at an attribute-level, including all the corresponding values in the dataset. This enables fast construction of visualizations. In contrast, iVoLVER operates at the level of individual data points, a lower level of data abstraction. With iVoLVER users are responsible for defining what is a data point, how it is mapped to a specific visual property, and how it is to be interpreted (e.g., as categorical or numerical data).

In Tableau, a single action typically affects all elements of the visualization regardless of whether the dataset contains a handful or millions of rows. Thus, Tableau typically does not require repeated interaction steps. In contrast, iVoLVER's paradigm of bottom-up construction forces users to apply operations per data value. Although it could be feasible to implement mechanisms to eliminate repetition through automation in constructive approaches (à la *programming by example* [6, 14, 28]), iVoLVER does not currently allow this.

Visual Representations as Controllers

iVoLVER is designed to blur the line between visual representations and their control and configuration. The dataset, controls, configurations, and visual elements all reside in an infinite canvas, and most widgets are both representations of data and allow its manipulation. In contrast, Tableau's pane-based interface separates manipulation and representation: the central visualization pane shows the results of operations spatially separated from the configuration areas of the interface. Access to some functionality takes place through menus.

To investigate the consequences of these two differing interface approaches we conducted two studies with non-experts: an in-classroom pilot study and a more in-depth lab study.

IN-CLASSROOM PILOT STUDY

Our pilot study was run as part of an introductory university course on information visualization. As part of this within-subjects study students were introduced to Tableau Desktop and iVoLVER in two subsequent tutorials that took place in weeks three and four of the 11-week course, immediately after a lecture on marks, visual variables, and mappings. Students completed three visualization exercises using each of the tools and provided feedback about their process, the character of visualizations they built, and their general experience with the tools. We describe the methodology, which is shared with our main study, in detail below.

Participants

Out of 36 students enrolled in the class, 19 volunteered to participate in the study. Of these, eight did not complete both study sessions, leaving us with 11 participants (7 male, 4 female; age 21–26, median 22). Only data from these students was considered in our analysis of findings. Participants had backgrounds in computer science, information technology, language & culture, and statistics. All of them were novices in InfoVis with varying self-reported expertise: four had no

prior knowledge about information visualization; four were aware of InfoVis through the web and/or magazines without knowledge about its theory; and three had been actively following visualization topics but did not have practical application experience.

Study Procedure

The study was divided into two sessions. In Session 1 all students of the course were split into two groups. One group was introduced to Tableau Desktop and the other to iVoLVER. In Session 2 (the following week), students switched tools. Each study session started with an introduction to Tableau Desktop or iVoLVER to the respective groups. Students then completed a set of tasks with the corresponding tool and dataset. We used one dataset on oil production and consumption levels and another about movies; each with five data points and five attributes. The tasks were to create three different visualizations addressing different aspects of the data. For the oil dataset we asked for visualizations about: oil production levels by country (V1); the countries and their regions (V2); the oil production, consumption and population by country (V3). The tasks for the movies dataset were equivalent in the type and number of attributes: V1 was about displaying the budget of each movie; V2 about genre; and V3 was about budget, world-wide gross revenue, and duration (see auxiliary material for the datasets and tasks). Students had 30 minutes to complete the tasks. To balance tasks, datasets and tools, participants in both groups saw the same datasets and tasks in the first session, and different (but equivalent in size and difficulty) datasets and tasks in the second.

After completing the tasks, participants filled out questionnaires about their satisfaction with the tool, the visualizations they created, and the rationale for their representation choices. They also rated the process of constructing visualizations with the tool and listed its most useful and problematic features. At the end of Session 2 we conducted a group discussion with all students, who compared their experiences with each tool and perceived benefits and drawbacks.

Data Collection & Analysis

We recorded 650 minutes of participants' visualization processes in the form of video screen captures. We analyzed the video through a qualitative video coding process as proposed by Heath et al. [19]. Specifically, we coded for visualization types, selected mappings, exploration of alternative designs, experimentation with features of the tool, and problems observed during the construction process.

Similarly, participants' statements from the questionnaires were categorized and analyzed using qualitative coding. Codes focused on design approaches, satisfaction level rationale, useful and problematic features, and benefits and limitations of the tools. The 17-minute group discussion at the end of Session 2 was audio-recorded and transcribed. The qualitative analysis of discussion statements focused on perceived differences, benefits and limitations of the tools.

Pilot Study Results

The analysis of the screen recordings gave us an initial understanding of the common sequences of actions participants carried out, the tool features they had problems with, and the extent to which they explored alternative designs. We found that

participants using Tableau Desktop explored more alternative designs than those using iVoLVER, but almost exclusively through the "Show-me" pane in something that appeared to be a trial-and-error approach. Also, the visualizations constructed in iVoLVER were more diverse than those created in Tableau and included non-standard visualizations.

Some of participants' motivations behind their design decisions can be inferred through their questionnaire responses: *"I just dragged and dropped the attributes and Tableau did the rest and I just kept moving them around until I found one I liked."* [s7], *"by exploring available chart types and then selecting them depending on the available properties/measures."* [s8, commenting about her vis approach in Tableau]. While these responses and our video analysis suggested a fundamental difference in both tools regarding how students' approached their visualization design, the brief nature and vagueness of the students' written comments in the questionnaire did not provide enough context for an in-depth analysis of the nature of these differences. For example, when asked how they decided on the visual mappings, one student answered *"Messing around."* [s9], and another wrote *"Different shapes, I like circles."* [s2].

During the group discussion conducted at the end of Session 2 students highlighted the benefits and limitations of both tools. In particular, they identified trade-offs, for example, between the level of automation (as provided by Tableau) and flexibility (provided by iVoLVER) and the interplay between these features. However, only six students actively contributed to this discussion, so this data is not representative.

Perhaps more importantly than its results, the pilot helped motivate and focus our research on several key questions: What characterizes and drives the overall visualization design process using the two tools? Do top-down and bottom-up construction approaches influence the visualization design decisions and the exploration of alternative designs and if so, how? How do non-experts experience these two approaches in comparison? Following up on this pilot, we conducted a study to explore these questions more in-depth.

IN-DEPTH COMPARISON OF IVO LVER & TABLEAU

Our in-depth comparative study of iVoLVER and Tableau Desktop followed a similar procedure as the pilot, but focused more on eliciting participants' individual perspectives on the tools which required one-on-one open-ended interviews. This study is therefore based on individual sessions, rather than an in-classroom setting.

Participants

We recruited ten participants (3 female, 7 male, 20–46 years old—median 28) from our university via word-of-mouth. None of them had participated in the pilot or ever taken an InfoVis course or any other training in visualization. Seven were undergrad or graduate students enrolled in computer science, mathematics, or physics; three were professionals with experience in teaching and/or researching in topics related to information technology, computer science, physics, and medical engineering. Two participants stated to have no knowledge of visualization, six reported having come across visualizations on the web and/or in magazines, but never considered

visualization concepts. One participant had been actively following and reading about visualization-related topics, but did not have any practical experience. Finally, one participant had been actively reading about the topic, and had experience in creating visualizations for at least one year. All participants stated to be familiar with reading graphs and charts, with six stating to have created some, and one stating to be frequently involved in creating graphs and charts and to be quite comfortable with it. Some participants had experience with common visualization tools—such as MS Excel (10), D3.js (1), and Processing (1)—and programming languages, such as Matlab (4) and Python (5). None of the ten participants had used Tableau Desktop before the study, but four had heard of it. One participant had used iVoLVER once, six had heard of it but never used it, and three did not know it at all. No participant had ever received formal instruction on visualization concepts such as marks and visual properties. Even the participant who had used D3.js, stated to have sparse conceptual knowledge on InfoVis. Participants received a £10 gift voucher.

Study Procedure

Each study session consisted of the following activities:

Introduction to Visualization Concepts. After filling out a questionnaire about their demographics and visualization expertise, each participant watched a 4-minute video³ explaining the fundamentals of the process of creating visual representations. The video explained the concepts of marks and visual variables and their relevance in the design and construction of visualizations. It also discussed how some visual variables are more (or less) effective for certain data attribute types. The video ended with a slide showing several standard visualizations encouraging participants to think about the composition of marks and their visual properties in these representations. Participants kept a printout summarizing the video to have at hand during the tasks (see auxiliary material for details). This stage ensured that all participants had at least some minimum knowledge on basic visualization concepts, similar to participants in the pilot who had seen these concepts as part of their InfoVis course.

Introduction to Tool. A 20-minute tool introduction session followed for the first tool (iVoLVER or Tableau Desktop) that included an overview of its interface features and a demonstration of how the tool implements the concepts of marks and visual variables, as well as the interactions steps required to map data to visuals. This live demonstration showed participants how the tool was used to create a visualization of a small dataset. Participants were provided with a printed “tool cheatsheet” (see auxiliary material for details) to help them in the subsequent visualization tasks.

Visualization Task. Participants received a dataset and tasks to complete identical to those in the pilot study (same data and tasks—see pilot above and the auxiliary material). Participants had 30 minutes to complete the tasks.

Feedback on Tool. Participants filled out a questionnaire rating their experience with the visualization tool, their satisfaction with the resulting visualizations, and their understanding

on the dataset after interacting with the tool. An open-ended interview followed where they described their visualizations, their creation process, their mapping choices, and their general experience and satisfaction with the tool and its features.

Participants went again through the sequence of intro-to-tool, visualization task, and feedback session with the second tool and the second set of data and tasks. Tool order was counterbalanced across participants to reduce learning effects and assure that each tool was tested the same number of times on each dataset and task. The study session concluded with a final interview where participants compared how iVoLVER and Tableau Desktop supported the visualization process and listed their perspectives on benefits and limitations of each tool. We also asked them if they would use any of the tools in the future and if so, for what types of visualization tasks. Each study session took approximately two hours.

Data Collection & Analysis

We used questionnaires to collect participant demographic and background information as well as their ratings of the visualization process and results. Questionnaire answers were coded and categorized according to themes such as design ideas, rationale for the choice of visualization type, visual mapping strategies, identified benefits and limitations of each tool, and potential usage scenarios.

We took written notes of participants’ interaction processes with the tools and video captures of all on-screen activities. In total, 415 minutes of video data were analyzed using qualitative methods as proposed by Heath et al. [19]. This included a characterization of the individual visualization steps and a detailed analysis of particularly interesting episodes flagged by the experimenter in the observational notes (e.g., patterns in the use of specific functionality and problematic interaction paths). We also collected the visualization outcomes (30 in Tableau and 28 in iVoLVER—two participants did not complete all tasks due to time constraints).

All interviews were audio recorded, fully transcribed and qualitatively coded by two researchers independently following a thematic analysis approach [8]. Initial coding focused on themes from the interview questions such as the visual mapping process and the benefits and limitations of the tools. From there, higher-level themes emerged, for example, suitable usage scenarios for each tool, and perceived ownership of the process and results. The scheme evolved through regular meetings of the researchers who discussed and refined the codes until the scheme stabilized.

FINDINGS

Figure 3 shows an overview of the visualizations created with both tools. Visual inspection supports an overall difference in the range of visualization types created with each tool.

iVoLVER. Participants created a large variety of visualization types for the three tasks. For V1, most participants (8/10) produced bar charts; two participants created a bubble chart. For V2 there was a strong preference for representing qualitative attributes with changes in shape and color (6/10); other visualization approaches included a Venn diagram (p1), a graph representation (p2), a table (p8), and a cluster-based visualization (p10). For V3, scatter plots constitute half of the vi-

³Available at <http://ivolver.cs.st-andrews.ac.uk/study>

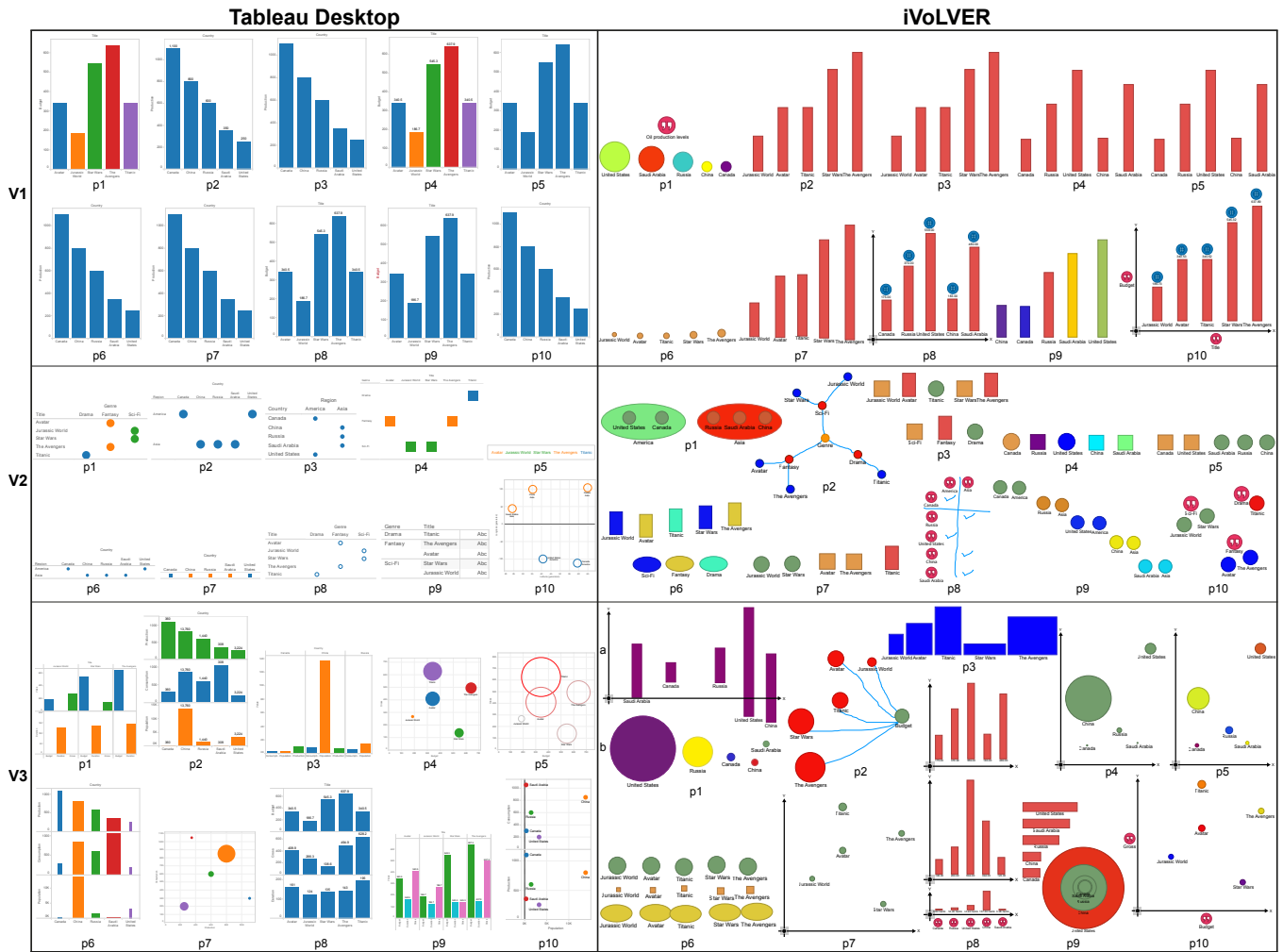


Figure 3. The visualizations built by participants of the main study, per task and tool, labelled according to participant number.

sualizations, together with one multi-bar chart (i.e., one bar chart for each attribute—p8), one unfinished graph representation (p2), and three non-standard visualizations where attributes were mapped to shape, color, and/or the width and height of rectangular marks (p3, p6, p9).

Tableau Desktop. Visualizations created in Tableau Desktop form a less heterogeneous set. All participants created bar charts for V1. The majority of visualization types created for V2 are matrix-like representations with marks located in cells (7/10), with the exception of one visualization containing colored text marks (p5), one text table (p9), and a scatter plot where the latitude and longitude auto-generated by Tableau were used to position circular colored marks to represent different countries (p10). V3 visualizations were split between multi-bar charts (6/10) and scatter plots (4/10).

The popularity of bar-based constructions visible in the visualization results of both tools is consistent with previous findings of novices constructing visualizations in Tableau with the assistance of an expert [18]. The entire set of designs also resembles the *representation continuum* discussed by Walny et al. in the context of data sketching [42], but our participants did not create line graphs or pictorial representations.

The Visualization Construction Process

The video and interview analyses revealed that participants approached their visualization construction process differently in iVoLVER and Tableau Desktop, as summarized in the sequence diagrams of Figure 4.

In *iVoLVER*, participants followed a mostly linear process (see Fig. 4.A). They reported that they first identified the *data attributes* relevant for the given task and then tried to come up with an *idea* of the type of visualization they wanted to build (e.g., a bar chart) or the types of marks they would use to represent the data (e.g., circles): “For the first design I just thought about all the general bar graphs that we see all the time in, you know, publications and stuff like that.” [p3].

Participants would then engage in a *representation process* trying to realize their initial idea. This process typically involved extracting relevant data points from the data table and mapping them directly onto the marks’ properties. However, some participants also reported creating first some marks and assigning them colors or labels, before connecting these marks to data points: “It’s like you’re pulling shapes into the thing in the same way you might in a drawing package. And only then are you kind of introducing data aspects.” [p5].

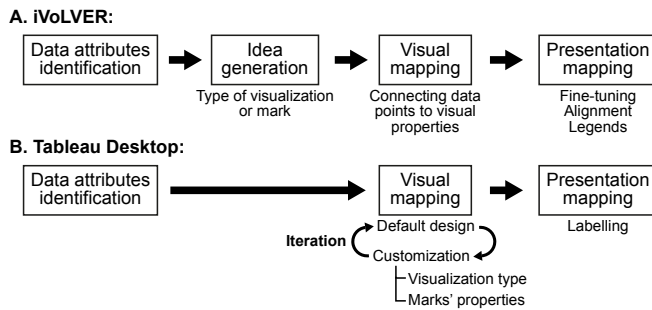


Figure 4. Stages of the observed visualization construction processes performed with iVoLVER (A) and Tableau Desktop (B).

Applying textual labels to marks referring on their corresponding data—typically discussed as a step of presentation mapping [26]—was an integral part of the representation process, as it allowed participants to keep track of what mark represented which data point. Participants would also position, align, or group their marks intentionally. Final layout adjustments and the creation of legends (2/10) concluded participants’ visualization construction process in iVoLVER.

What stands out in this process is its linearity. The exploration of alternative visualization designs or iterating on initial ideas was rare with only one participant attempting to construct different designs in iVoLVER (see p1 for V3 in Fig. 3). Exploration was mostly done in the context of testing the suitability of a representation idea, for example, a particular mapping using a single data point and a single mark. Participants’ statements indicate that it was the elaborate construction process that prevented them from further design iterations or explorations in iVoLVER: “Many things need to be manually done. For example, even for these five marks I need to drag fifteen times. [...] But if, after I drag fifteen times, I realize ‘no, a bar chart is not good’ and I need to change. Then, probably it would be quite difficult to change at that time.” [p8].

In **Tableau Desktop**, as with iVoLVER, participants first identified the *data attributes* relevant to their task. However, they then typically started the *representation process* right away, dragging the attributes of interest into the rows and columns shelves, even if they did not have an idea in mind about how to represent these attributes. Only two participants reported having an initial idea before they started to explore visualization types in Tableau Desktop. Participants typically followed Tableau’s default suggestions for their initial visualization design (visible in the Tableau visualizations for V1 and V2 in Fig. 3) and spent most of their representation process customizing this design (e.g., changing shapes or colors).

In contrast to iVoLVER, we found the representation process in Tableau Desktop to be more iterative, with participants experimenting with the mapping of attributes to visual elements and rearranging the attributes in the rows and column shelves to redefine existing mappings. Many participants also made use of the “Show me” pane to explore alternative visualization types, however, we observed this type of exploration much less frequently than in the classroom context of the pilot study. These notable differences in the sequence of actions confirm the results of previous studies that compared approaches of constructing bar charts using template-based digital tools and physical tiles [44].

The Tools’ Influence on the Design Approach

When it comes to constructing visualizations, coming up with ideas on how to visually encode data is key. During the interviews, we prompted participants to comment on how they carried out their mappings and what drove this process. As shown in Figure 3, we found that the two tools heavily influenced participants’ approaches to visualization design.

With **iVoLVER** participants typically reported to have a design idea in mind and only then to start the practical process of mapping data to visuals. They often mentioned the need to plan and/or think before engaging into the representation process—this was experienced as challenging, but also encouraged creativity: “In iVoLVER there is sort of an extra step where you actually have to come up with the plot itself and the strategy to build it. [...] When you say ‘I wanna do bar charts’ in iVoLVER, you have to think of stuff like ‘OK, so. How am I going to order the bars?’, ‘How am I gonna connect?’ It’s up to you, all kind of different things: ‘Am I gonna scale the data?’” [p2]; “[In iVoLVER] you have to think about the properties in one sense but also the marks. And it’s slightly more creative because you are making that selection, before you’re seeing a bar chart or a graph or something that’s quite default and typical.” [p9].

In contrast, the exploration of designs in **Tableau Desktop** was tool-driven, as shown by the video analysis and interviews. The process was characterized by participants following Tableau’s design lead in the absence of an initial idea or reflection on adequate data mappings: “I mean, I don’t really have to think about it [the design] in any way. I just put the title in one column and the value in the rows and, you know, that automatically created the bar chart, which is perfectly adequate. [...] I didn’t necessarily have a bar chart in mind. I just wanted to put it there and decide later on how it’s best represented depending on what the program does. [...] And then see where to go from there.” [p1].

Six participants mentioned or suggested this notion of “no-need-to-think” when working in Tableau: “I was just dragging values around like ‘Oh, I’ll put this in the columns’, ‘I’ll put this in the rows’, ‘I’ll change this mapping from this thing’, but without really thinking about it.” [p5]; “It feels like a very quick and easy way of presenting some simple data if you don’t have time to think about how you want to do it in a different way.” [p9]. One participant directly compared the design process of the two tools—their conclusions are representative: “I really, really, liked the way that I can very quickly get something going [in Tableau]. I felt that [...] I didn’t have to think as much about how to implement it, as I did in iVoLVER.” [p5]. These statements confirm what our video analyses of the construction processes in both the pilot and the main study hinted at: with Tableau Desktop participants experimented rapidly with a range of different design approaches, but typically without much critical reflection.

The impact of this tool-driven approach seen with Tableau should not be underestimated; we have evidence that it can fundamentally influence the way in which people think about visualization design—even if they do not use the tool any longer. Three out of five participants who worked first with Tableau stated that their decisions on visualizations types in

iVoLVER were based on what they did with Tableau: *“Because I did the previous experiment using Tableau. The datasets are quite similar, so I already had in my mind, it should be something like a bar chart, because I did the previous experiment.”* [p8]. In fact, when working with iVoLVER, this participant replicated all the visualizations he previously built with Tableau Desktop. We did not find any evidence that working with iVoLVER influenced design choices in Tableau.

Design Exploration

The fundamentally different approaches to visualization design represented by the tools also have an influence on how and how much participants explored alternative design ideas. The speedy, tool-driven process in **Tableau Desktop** promoted the exploration of multiple mappings as indicated by the following statements: *“Since there are so many options, you want to try putting data in different slots and try different kinds of graphs in order to see what looks better. In a way that’s good because you get to explore more stuff.”* [p3]; *“I can change from bars to other things quite easily. [...] so, I can quickly experiment with different charts and see the final one. But for iVoLVER I need to decide first and then I choose the bar chart.”* [p8]. As mentioned earlier, with iVoLVER participants typically did not iterate on their visualization designs once they had built them, neither did they explore different visualization types (see Fig. 4).

However, the type of exploration promoted by Tableau seems less in-depth compared to iVoLVER, with participants not critically reflecting on the meaning and potential impact of their explorations: *“There wasn’t any need to do anything else because what [Tableau] did automatically was what I should have done, I suppose.”* [p1]; *“Because it takes care of so much for you, you sort of have to build up a good set of experience to use it. You know, to just be able to expect what it will do.”* [p2]. Furthermore, the tool-driven exploration hampered participants’ experimentation with their own ideas: *“I think because it’s quite automated, sometimes it’s perhaps a bit more difficult to customize things in the way that you want to.”* [p1]; *“It felt like I wasn’t really composing the thing. I was kind of putting stuff into pre-canned visualizations.”* [p5]. While design explorations can be laborious in iVoLVER, they allow for more free-form, creative experimentation and critical reflection. With iVoLVER we observed a more “thoughtful” approach to visualization design exploration: *“And I think the process [in iVoLVER] is very much an atomic thing. So, you do know ‘OK, this one is bigger than this one’, because you’re dragging it and you’re doing it. And so you’re thinking about the values of each thing you are putting on consciously rather than just assuming.”* [p10].

Deciding on Visual Mappings

The visualization design process not only includes coming up with an idea of how to represent the data as a whole (e.g., the type of visualization) but also how to encode particular attributes using visual variables such as size, color, or shape. According to participants’ statements these low-level visual mappings were typically a consequence of the visualization type chosen: *“I chose bar charts and, of course, the height is the suitable [visual variable].”* [p8, about his process with iVoLVER]. However, most participants, regardless

of the tool, were able to justify their decisions on visual mappings by reflecting on the suitability of certain visual variables to encode particular attribute types. For example, working with Tableau, participants stated things like: *“The budget is quantitative, so I used length.”* [p4]. Statements after using iVoLVER go in a similar direction: *“I decided on color because it seemed like a good way to represent categorical data.”* [p5]. These statements, which link to what participants learnt through our introductory video, indicate that in both tools they were able to apply visual mappings they came up with for their visualization.

Manipulating Data and Associated Visual Elements

iVoLVER and Tableau Desktop represent opposite extremes in the bottom-up/top-down vis construction spectrum, and the consequences are reflected in the interviews. Participants discussed iVoLVER’s bottom-up strategy as laborious because it requires manipulating every single data value: *“For every circle I had to do the same, the same, the same thing. So, if there was a way I just do it for one circle, and it automatically does it for all the circles around—it would be perfect.”* [p7]. However, they also highlighted flexibility and freedom as benefits of the bottom-up approach: *“Because of the way iVoLVER presents all the values you can change all of the direct mappings. I can kind of be a bit more creative with them. [...] Perhaps a good example would be that in the case of the third activity it was very, very easy to see that I could map one value to the height and one value to the width.”* [p3]; *“[iVoLVER] was actually much more free and helped me come up with new ideas. In Tableau I had no idea what to do with that type of [categorical] data and there wasn’t a huge amount of freedom to play. Whereas here [in iVoLVER], moving the actual atomic data points and figuring out ‘OK, this isn’t linear [...] How do I move them and group them?’”* [p10].

The above statements highlight what we believe is an important trade-off: Tableau’s top-down approach results in very few required interactions allowing for the speedy creation and exploration of different visualization types. However, this comes at the cost of transparency of the visualization process. When working with Tableau, it was sometimes difficult for participants to follow how data was mapped to the visual properties of marks, in contrast to iVoLVER where this connection is clearly visible. Along these lines, one participant stated: *“iVoLVER is better for design because you actually get to see what works, what doesn’t work and why. Whereas in Tableau I don’t think you get to see what works and doesn’t work and why [...] because it’s generated so quickly that you don’t get the sense of something building up. Whereas in iVoLVER you’ve built something up from a quite low level. Whereas in Tableau you just come in and something is created. You don’t see how it is created or why.”* [p10].

In general, most visualization features in Tableau are connected on an attribute-level; manipulating them can introduce fundamental changes in the visualization that can be difficult to follow. Commenting on their experience with the “Show me” pane, one participant stated: *“At one point I clicked on it, and it changed everything. I was like ‘This is a disaster!’ [...] I was just not quite sure what it was going to do once I put genre in columns. It was just very abstract.”* [p4]. This, along

with previous statements, makes clear that predicting, keeping track of, and interpreting exactly how Tableau Desktop maps data to visual properties was often difficult for participants due to the speed and the attribute-level scale in which things change based on user's interactions. That being said, the links that show the mappings between data and visuals in iVoLVER, while adding transparency, also frequently cluttered the interface and, therefore, hampered the visualization process. Four participants mentioned this explicitly: "You get to a certain level of complexity, it becomes very hard to manage all connections." [p5]; "You have the connections, which, again, are quite confusing sometimes. Again, you have to keep good track of what you have done so far." [p1].

Control and Authorship

The type of words participants used when describing their visualization process in Tableau vs. iVoLVER further indicates that the visualization process in Tableau is largely tool-driven. When explaining their iVoLVER constructions, all participants assumed authorship of the process and outcomes. This was visible in the use of first person singular personal pronouns (e.g., "I did", "I mapped"), as the following statement illustrates: "And the third [vis] I'm satisfied with because I showed different data in, like, a readable way." [p4]. Across all interviews, in just a single instance was iVoLVER credited with a design decision: when a participant released a connection on top of a circular mark and iVoLVER associated this to the mark's radius property (its default behavior). In contrast, in their descriptions of the process with Tableau most participants (8/10) at some point accredited Tableau the responsibility for certain design decisions: "Tableau did a very good job of ordering them. For example, now we know what Canada produces." [p6]. It was also common for participants to describe their visualization results as a consequence of a mix of their own and Tableau's actions which they clearly separated, as illustrated in this exemplary statement: "I dragged the title and I dragged the gross here. Then it automatically generated this [vis], which I think is good enough. I can understand this already and, again, I wanted to add the labels to make it easier to read. [...] So, I tried to drag the label." [p8].

Authorship was also explicitly commented on (unprompted by us) by six participants when summarizing their experience with the two tools: "[In] Tableau you just throw it at the system; throw everything and then it generates for you" [p8]. And commenting on iVoLVER: "I'd say that the process [in iVoLVER] is definitely more involved in that you have to actually interact with that data instead of just throwing the idea of a column into a thing and having it built for you. [...] Because designing is something that you need to be involved in, and you need to understand what's happening with the data for you to show what's happening with the data." [p4].

Overall Preferences

At the end of each study session, we asked participants' what tool they preferred overall. Most of them favored Tableau Desktop (7/10) because of the speed of construction. However, two of these seven also mentioned a trade-off between speed and: 1) opportunities to explore ("I did everything quicker in Tableau, even though there was less space for exploration." [p3]; and 2) experiencing the process ("Because

I am writing papers, I just want to see the result; I don't need the process. So, Tableau would be better. But if sometimes I need the process I might choose iVoLVER." [p8]). One participant preferred iVoLVER because of its flexibility, but considered Tableau her default option because of its speed: "I'm a very visual user. So, although I got a bit stuck with iVoLVER, I would probably persevere with it just because it let me drag and play around and I could quickly see changing shapes and objects and things like that. But I could see me defaulting to Tableau if I have to quickly create a graph." [p9].

As indicated by these statements, all participants found the tools' suitability to be context dependent. Tableau is convenient when dealing with large datasets: "I'd probably prefer Tableau because I generally use large datasets, and in a large dataset iVoLVER is just not gonna handle it. And so, Tableau would be the only viable option." [p10]. iVoLVER was considered useful for prototyping, for exploring unfamiliar datasets, and for more creative approaches to visualization: "iVoLVER could be a really powerful tool to prototype visualizations because of its generality and because it's really convenient and really transparent." [p2]; "I would say [iVoLVER] is much more useful probably with more unique types of visualizations. Something that isn't just a standard chart; something where you want to have that fine grained control; and something where you aren't super familiar with the dataset and you want to figure it out as you go." [p4].

Two participants mentioned a hybrid approach using both tools. They identified iVoLVER as a good starting point to experiment with potential designs and Tableau Desktop as preferable for implementing the visualization once the design has been decided: "If I don't know what I want yet, I would prefer to try iVoLVER first to see in how many ways I can design the visualization. And then, if I know what I actually want already, I would just put it on Tableau because it's faster." [p7]; "I would use iVoLVER for quick drafts of data visualizations. And then if I had to do maybe a more professional one, then maybe move to Tableau." [p3].

Teaching and Learning InfoVis

Because of its predefined templates, one participant mentioned Tableau as a good tool to teach people the design space of standard visualizations: "If you're sort of learning a taxonomy of different types of visualizations, Tableau is probably better because they already exist, and you can experiment very quickly by just moving a few things around." [p5].

Conversely, iVoLVER was mentioned as useful to train beginners because of its transparency regarding the visualization process which brings across basic visualization concepts: "If I was trying to show people the ideas and the intuition and the motivation behind visualizing things, definitely iVoLVER. Once again, the triviality and the transparency [of the process] are the two winning factors." [p2]; "Because it's more intuitive. At least I believe that in order to learn something, you have to get your hands dirty; you actually have to go and see. The level of automation of Tableau is very high. It's just like drag, and then you have no idea what would happen. For iVoLVER you can influence directly what will happen. [...] I believe that for a beginner iVoLVER is better than

Tableau.” [p7]; “Tableau does it for you, which isn’t helpful at any kind of education system. Because you don’t have to figure out what specifically is happening and how position works and how area works. It’s just sort of you drag it into size and—whoop!—it does it. Whereas in iVoLVER you need to actually pay attention.” [p4].

DISCUSSION

Our findings show important differences between the two tools in outcomes, process, design approach, authorship, and preference. Participants recognized Tableau Desktop as an efficient tool, but often used it in a haphazard way—“no thinking required”. Although the visualization process in Tableau Desktop included more alternatives, visualization outcomes were also more homogeneous. The analysis also shows that participants using iVoLVER initiated the design process with their own ideas whereas Tableau users were strongly led by this tool’s design suggestions. Although most participants preferred Tableau Desktop for its speed (7/10), the consensus was that iVoLVER facilitated an understanding of the visualization process and promoted a feeling of authorship.

Efficiency vs. Understanding, Freedom and Creativity

The comparison of the two tools highlights the consequences of bottom-up and top-down visualization construction approaches on process and outcomes, which is relevant for designers of visualization tools for non-experts. The trade-offs are remarkably tricky; Tableau’s top-down approach allows people to quickly explore many alternative designs compared to the more laborious bottom-up constructive process in iVoLVER. This reflects the tension between magic and literalism identified long ago by Smith [38], but it goes further: the efficiency of the top-down template-based or shelf configuration approaches might come at the cost of thoughtfulness and affect the transparency of the process. When participants are forced to construct a visualization from the ground up (i.e., from the level of data points), they seem to be involved in a deeper process that results in a better understanding of how the visualization evolves and in a feeling of control, ultimately leading to more creative and varied designs and a stronger experience of authorship.

In many situations tools need to be, first and foremost, quick and efficient; however, it is important to recognize that visualization design is also a creative task. There is value in enhancing the breadth of people’s explorations for visualizations that support their own purposes. Similarly, promoting “thoughtful exploration” and a thorough understanding of the consequences of representation design decisions is more in line with the goals of visual literacy [7, 20, 30], and is an important part in educational contexts. This is in stark contrast to “black boxing” functionality that might leave important decisions to the software.

The Space in Between

Tableau Desktop and iVoLVER represent two extremes of the spectrum of vis construction approaches. Tools that allow “mode switches” between these two philosophies, or hybrid approaches that bridge the idea of template-based, shelf configuration and constructive approaches may maximize the benefits and overcome the disadvantages of each approach.

However, finding a sweet spot that balances the trade-offs we have described requires more research; although it would be relatively easily to speed up iVoLVER with more abstract dataset operations, this very act of repetitive hands-on data mapping might be what provides the sense of thoughtfulness, creativity and authorship we observed. Additionally, increasing automation might reduce the transparency of the process and harm its understanding [21]. Exploring the design space in-between seems a promising avenue for future research.

LIMITATIONS AND OPEN QUESTIONS

The design choices of our studies obviously impact the generalizability and validity of the presented results. First, we have studied only two particular tools with their own idiosyncrasies and workflows that we believe represent two ends of the top-down/bottom-up spectrum. Second, carrying out a controlled experiment in which we imposed particular datasets and tasks may have affected participants’ process and visualization approach. While this effect has to be considered when extrapolating our findings, we believe that most of our observations can be linked to the tools’ general approach rather than the specifics of our study. For example, our participants highlighted the importance of the visibility and flexibility of the visualization design process regardless of the particular implementation of each tool. Without prompting participants commented on how the tools would scale (or not) with bigger datasets. Nevertheless, additional studies are required that investigate our research questions considering additional visualization tools and different (sizes of) datasets and analysis tasks.

We must also highlight that our participants all had a science background and therefore arguably an affinity to quantitative data analysis, which may have influenced our findings. Additional studies should investigate if and how our findings expand to different populations (e.g., with a background in the arts or humanities) and age groups (e.g., teenagers and seniors). We believe that these new questions need to be addressed through further studies which, in combination with advances in the design and implementation of new visualization tools, will offer a more definitive emerging picture.

CONCLUSION

We have presented a qualitative study that compared how non-experts design and implement visual representations with a top-down and a bottom-up visualization tool. We identified differences in how these approaches shape people’s visualization process, decisions and justifications regarding the visual representation of data, and people’s experience and their feeling of control and authorship toward the visualization outcomes. Our insights inform the design of future visualization tools that are fast and easy to use but also empower people to create effective visualizations and promote critical thinking on their design.

ACKNOWLEDGMENTS

We thank the study participants, the reviewers, and SACHI members for their feedback and help. The Ecuadorian Government supports Gonzalo Gabriel Méndez through a SENESCYT scholarship.

REFERENCES

1. Greg Abram and Lloyd Treinish. 1995. An Extended Data-Flow Architecture for Data Analysis and Visualization. In *Proceedings of the 6th Conference on Visualization '95 (VIS '95)*. IEEE Computer Society, Washington, DC, USA, 263–. <http://dl.acm.org/citation.cfm?id=832271.833845>
2. Edith Ackermann. 2001. Piagets constructivism, Paperts constructionism: Whats the difference. *Future of learning group publication* 5, 3 (2001), 438.
3. Jaques Bertin. 1999. *Readings in Information Visualization*. Morgan Kaufmann Publishers Inc., San Francisco, CA, USA, Chapter Graphics and Graphic Information Processing, 62–65. <http://dl.acm.org/citation.cfm?id=300679.300683>
4. Jacques Bertin. 2010. *Semiology of Graphics: Diagrams, Networks, Maps* (1 edition ed.). ESRI Press, Redlands, Calif.
5. Alex Bigelow, Steven Drucker, Danyel Fisher, and Miriah Meyer. 2014. Reflections on How Designers Design with Data. In *Proceedings of the 2014 International Working Conference on Advanced Visual Interfaces (AVI '14)*. ACM, New York, NY, USA, 17–24. DOI: <http://dx.doi.org/10.1145/2598153.2598175>
6. Alan F. Blackwell. 2006. *Psychological Issues in End-User Programming*. Springer Netherlands, Dordrecht, 9–30. DOI: http://dx.doi.org/10.1007/1-4020-5386-X_2
7. Jeremy Boy, Ronald A. Rensink, Enrico Bertini, and Jean-Daniel Fekete. 2014. A Principled Way of Assessing Visualization Literacy. *IEEE Transactions on Visualization and Computer Graphics* 20, 12 (Dec 2014), 1963–1972. DOI: <http://dx.doi.org/10.1109/TVCG.2014.2346984>
8. Richard E Boyatzis. 1998. *Transforming qualitative information: Thematic analysis and code development*. Sage.
9. Stuart K. Card and Jock Mackinlay. 1997. The structure of the information visualization design space. In *Information Visualization, 1997. Proceedings., IEEE Symposium on*. 92–99. DOI: <http://dx.doi.org/10.1109/INFVIS.1997.636792>
10. Stuart K Card, Jock D Mackinlay, and Ben Shneiderman. 1999. *Readings in information visualization: using vision to think*. Morgan Kaufmann.
11. Ed H. Chi. 2000. A taxonomy of visualization techniques using the data state reference model. In *Information Visualization, 2000. InfoVis 2000. IEEE Symposium on*. 69–75. DOI: <http://dx.doi.org/10.1109/INFVIS.2000.885092>
12. William S Cleveland and Robert McGill. 1984. Graphical Perception: Theory, Experimentation, and Application to the Development of Graphical Methods. *J. Amer. Statist. Assoc.* 79, 387 (1984), 531–554. DOI: <http://dx.doi.org/10.2307/2288400>
13. William S. Cleveland and Robert McGill. 1987. Graphical Perception: The Visual Decoding of Quantitative Information on Graphical Displays of Data. *Journal of the Royal Statistical Society. Series A (General)* 150, 3 (1987), pp. 192–229. <http://www.jstor.org/stable/2981473>
14. Allen Cypher and Daniel Conrad Halbert. 1993. *Watch what I do: programming by demonstration*. MIT press.
15. Selan dos Santos and Ken Brodlie. 2004. Gaining understanding of multivariate and multidimensional data through visualization. *Computers & Graphics* 28, 3 (2004), 311 – 325. DOI: <http://dx.doi.org/10.1016/j.cag.2004.03.013>
16. Niklas Elmqvist, John Stasko, and Philippas Tsigas. 2008. DataMeadow: A Visual Canvas for Analysis of Large-scale Multivariate Data. *Information Visualization* 7, 1 (March 2008), 18–33. DOI: <http://dx.doi.org/10.1145/1391107.1391110>
17. Lars Grammel, Chris Bennett, Melanie Tory, and Margaret-Anne Storey. 2013. A Survey of Visualization Construction User Interfaces. In *EuroVis - Short Papers*, Mario Hlawitschka and Tino Weinkauff (Eds.). The Eurographics Association. DOI: <http://dx.doi.org/10.2312/PE.EuroVisShort.EuroVisShort2013.019-023>
18. Lars Grammel, Melanie Tory, and Margaret-Anne Storey. 2010. How Information Visualization Novices Construct Visualizations. *IEEE Transactions on Visualization and Computer Graphics* 16, 6 (Nov 2010), 943–952. DOI: <http://dx.doi.org/10.1109/TVCG.2010.164>
19. Christian Heath, Jon Hindmarsh, and Paul Luff. 2010. *Video in qualitative research*. Sage Publications.
20. John A Hortin. 1980. *Visual Literacy and Visual Thinking*. (1980).
21. Jessica Hullman, Eytan Adar, and Priti Shah. 2011. Benefitting InfoVis with Visual Difficulties. *IEEE Transactions on Visualization and Computer Graphics* 17, 12 (Dec 2011), 2213–2222. DOI: <http://dx.doi.org/10.1109/TVCG.2011.175>
22. Samuel Huron. 2014. *Constructive Visualization : A token-based paradigm allowing to assemble dynamic visual representation for non-experts*. Theses. Université Paris Sud - Paris XI. <https://tel.archives-ouvertes.fr/tel-01126892>
23. Samuel Huron, Sheelagh Carpendale, Alice Thudt, Anthony Tang, and Michael Mauerer. 2014a. Constructive Visualization. In *Proceedings of the 2014 Conference on Designing Interactive Systems (DIS '14)*. ACM, New York, NY, USA, 433–442. DOI: <http://dx.doi.org/10.1145/2598510.2598566>

24. Samuel Huron, Yvonne Jansen, and Sheelagh Carpendale. 2014b. Constructing Visual Representations: Investigating the Use of Tangible Tokens. *Visualization and Computer Graphics, IEEE Transactions on* 20, 12 (Dec 2014), 2102–2111. DOI : <http://dx.doi.org/10.1109/TVCG.2014.2346292>
25. Samuel Huron, Alice Thudt, Bon Adriel Aseniero, Anthony Tang, and Sheelagh Carpendale. 2016. Constructive Visualization: A New Paradigm to Empower People to Author Visualization. In *SURFNET / Designing Digital Surface Applications*, Frank Maurer (Ed.). NSERC Surfnet, University of Calgary, Chapter 9, 169–191. <http://dspace.ucalgary.ca/handle/1880/50450>
26. Yvonne Jansen and Pierre Dragicevic. 2013. An Interaction Model for Visualizations Beyond The Desktop. *IEEE Transactions on Visualization and Computer Graphics* 19, 12 (Dec 2013), 2396–2405. DOI : <http://dx.doi.org/10.1109/TVCG.2013.134>
27. Waqas Javed and Niklas Elmqvist. 2013. ExPlates: Spatializing Interactive Analysis to Scaffold Visual Exploration. *Computer Graphics Forum* 32, 3pt4 (2013), 441–450. DOI : <http://dx.doi.org/10.1111/cgf.12131>
28. Henry Lieberman. 2000. Your wish is my command: Giving users the power to instruct their software. *Morgen Kaufmann* (2000).
29. Kwan-Liu Ma. 1999. Image Graphs - a Novel Approach to Visual Data Exploration. In *Proceedings of the Conference on Visualization '99: Celebrating Ten Years (VIS '99)*. IEEE Computer Society Press, Los Alamitos, CA, USA, 81–88. <http://dl.acm.org/citation.cfm?id=319351.319360>
30. Adam V Maltese, Joseph A Harsh, and Dubravka Svetina. 2015. Data visualization literacy: investigating data interpretation along the novice–expert continuum. *Journal of College Science Teaching* 45, 1 (2015), 84.
31. Gonzalo Gabriel Méndez, Miguel A. Nacenta, and Sebastien Vandenheste. 2016. iVoLVER: Interactive Visual Language for Visualization Extraction and Reconstruction. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems (CHI '16)*. ACM, New York, NY, USA, 4073–4085. DOI : <http://dx.doi.org/10.1145/2858036.2858435>
32. Tamara Munzner. 2014. *Visualization Analysis and Design* (har/psc edition ed.). A K Peters/CRC Press, Boca Raton. <http://www.cs.ubc.ca/~tmm/vadbook>
33. Kostas Pantazos and Søren Lauesen. 2012. Constructing Visualizations with InfoVis Tools-An Evaluation from a user Perspective. *GRAPP/IVAPP 2012* (2012), 731–736.
34. Seymour Papert and Idit Harel. 1991. Situating Constructionism. In *Constructionism*. Ablex Publishing Corporation.
35. Jean Piaget. 2013. *Child's Conception of Space: Selected Works*. Vol. 4. Routledge.
36. Jonathan C. Roberts, Chris Headleand, and Panagiotis D. Ritsos. 2016. Sketching Designs Using the Five Design-Sheet Methodology. *IEEE Transactions on Visualization and Computer Graphics* 22, 1 (Jan 2016), 419–428. DOI : <http://dx.doi.org/10.1109/TVCG.2015.2467271>
37. Arvind Satyanarayan and Jeffrey Heer. 2014. Lyra: An Interactive Visualization Design Environment. *Computer Graphics Forum* 33, 3 (June 2014), 351–360. DOI : <http://dx.doi.org/10.1111/cgf.12391>
38. Randall B. Smith. 1987. Experiences with the Alternate Reality Kit: An Example of the Tension Between Literalism and Magic. In *Proceedings of the SIGCHI/GI Conference on Human Factors in Computing Systems and Graphics Interface (CHI '87)*. ACM, New York, NY, USA, 61–67. DOI : <http://dx.doi.org/10.1145/29933.30861>
39. Robert Spence. 2001. *Information visualization*. Vol. 1. Springer.
40. Bret Victor. 2013. Drawing Dynamic Visualizations. Recorded at the Stanford HCI seminar. (2013). <https://vimeo.com/66085662>
41. Fernanda B. Viegas, Martin Wattenberg, Frank van Ham, Jesse Kriss, and Matt McKeon. 2007. ManyEyes: a Site for Visualization at Internet Scale. *IEEE Transactions on Visualization and Computer Graphics* 13, 6 (Nov. 2007), 1121–1128. DOI : <http://dx.doi.org/10.1109/TVCG.2007.70577>
42. Jagoda Walny, Samuel Huron, and Sheelagh Carpendale. 2015. An Exploratory Study of Data Sketching for Visual Representation. *Computer Graphics Forum* 34, 3 (2015), 231–240. DOI : <http://dx.doi.org/10.1111/cgf.12635>
43. Colin Ware. 2010. *Visual thinking: For design*. Morgan Kaufmann.
44. Tiffany Wun, Jennifer Payne, Samuel Huron, and Sheelagh Carpendale. 2016. Comparing Bar Chart Authoring with Microsoft Excel and Tangible Tiles. *Computer Graphics Forum* (2016). DOI : <http://dx.doi.org/10.1111/cgf.12887>