

Vistorian Analytics dashboard: Analyzing user interaction logs for interactive network visualization

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Abstract

Through decades of work, researchers in the visualization community have actively searched for a structural way to evaluate usage of visualization systems. The interaction logs of InfoVis systems can be a powerful quantitative tool towards evaluation analysis. This thesis based on data set collected from Vistorian tool, an open-source web-based platform that allows users to create different views of network visualization. We see the design opportunity to use an analytical dashboard to present live logging data for expert analysts, allowing them to see the complex data at a glance from different perspectives. Therefore, we present Vistorian Dashboard, a three-page interactive dashboard display depicting overall user activity, visualization diagram comparison and individual session timeline. By explaining the complete design process, this thesis demonstrates how to employ task analysis and iterative design methodology in dashboards, how to use dashboard design patterns and real data evaluation to finalize design decisions. Hopefully, this case study can benefit future research in visualizing logging data and generalized dashboard design.

Research Ethics Approval

This project was planned in accordance with the Informatics Research Ethics policy. It did not involve any aspects that required approval from the Informatics Research Ethics committee.

Declaration

I declare that this thesis was composed by myself, that the work contained herein is my own except where explicitly stated otherwise in the text, and that this work has not been submitted for any other degree or professional qualification except as specified.

(Jinrui Wang)

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Table of Contents

| | | |
|----------|--|-----------|
| 1 | Introduction | 1 |
| 1.1 | Research background | 1 |
| 1.2 | Motivation, research objectives | 3 |
| 1.3 | Problem statement, research questions | 4 |
| 1.4 | Methods, Intended contributions | 4 |
| 1.5 | Thesis outline | 5 |
| 2 | Related work | 7 |
| 2.1 | Evaluating user interaction in visual analysis | 7 |
| 2.2 | Visualizing user interaction logs | 9 |
| 2.3 | Dashboard design potential | 10 |
| 3 | Methodology | 12 |
| 3.1 | The Vistorian Dataset | 12 |
| 3.2 | Task analysis sessions | 13 |
| 3.3 | Iterative dashboard design | 14 |
| 4 | Vistorian Dashboard | 17 |
| 4.1 | Page compositions | 17 |
| 4.2 | Page: General overview | 19 |
| 4.3 | Page Visualization | 23 |
| 4.4 | Page User | 27 |
| 5 | Implementation | 31 |
| 5.1 | Skeleton in html | 31 |
| 5.2 | Building blocks in Vega-lite | 32 |
| 5.3 | User session timeline in D3.js | 33 |

| | | |
|----------|--|-----------|
| 6 | Evaluation and discoveries | 35 |
| 6.1 | Evaluation methods | 35 |
| 6.2 | Evaluation results about usability | 36 |
| 6.3 | Evaluation results about task analysis | 37 |
| 7 | Discussion | 42 |
| 7.1 | Analytical dashboard supporting visualization evaluation | 42 |
| 7.2 | Reflection for effective dashboard design | 43 |
| 7.3 | Limitations | 44 |
| 7.4 | Future work | 44 |
| 8 | Conclusion | 46 |
| | Bibliography | 47 |

Chapter 1

Introduction

1.1 Research background

The increasing number of Information Visualization systems (InfoVis) in recent years allows general users and academic researchers from various disciplines to conduct visual analyses of their data. In the visualization community, scholars are iterating InfoVis systems designs to better support user exploration. These systems benefit users through powerful visual representation selection and rich interaction techniques, through which users freely engage in dialogues with their data to unfold facts and insights [1]. Because of the heterogeneity of user groups, non-expert users differ significantly from advanced users in conducting their research. Additionally, people in the wild have various objectives when using InfoVis systems, which increases uncertainty and makes it more challenging for researchers to design experiments.

As such, visualization researchers have been actively searching for systematic ways to evaluate the usage of these InfoVis systems. On the user end, mostly controlled user experiments with lists of tasks and interview questions are designed to probe their behaviors [2]. In the context of InfoVis systems, academics have created taxonomies to group interaction strategies to help the quantitative analysis of user interactions [3, 4]. Interaction tracking data is a useful technique for capturing user sessions among the quantitative measures. Logs have the capacity to store a lot of user data for a variety of time frames. Researchers can design logging procedures to meet their needs for studies with a variety of goals. The collected logs will guide us towards user exploration patterns, systems advantages and flaws, and more insightful findings.

InfoVis tool: The Vistorian Networks

We focus our study for this dissertation on interactive network visualizations across all visualization fields. Networks can visualize complicated interactions, which is essential for humanities studies, but they also need users to have a higher level of visualization literacy to construct or comprehend. It is of significance to study how users explore networks.



Figure 1.1: Vistorian network tool

The Vistorian tool [5] supports networks with temporal features, including four main views of the node-link diagram, timeline node-link, matrix, geolocation map, and a coordinated view where users can navigate and compare two different views (see Figure 1.1). The open-source tool insists on the simplicity of data formation that it does not require users' coding knowledge to clean or format the data sheets. It also provides a thorough explanation of the acceptable data format for creating networks for those who are not visualization experts.

The core features of Vistorian allow high freedom to explore visualizations to support their works. Users can play with data freely with interactive features in the interfaces after successfully generating the diagrams: brushing the timeline, panning through the networks, changing visual representation to explore patterns, and filtering data selection to shift visualization focus. For the visualization researcher's side, the rich interactivity makes it an excellent choice to study users' visual exploration journey in the wild [6, 7].

Logging data in the wild

This dissertation investigates logging data in the wild, unlike most controlled investigations in lab settings. Regardless of the dataset utilized or the tasks carried out, data in the wild incorporates various user groups and purposes, providing analysts with a

complete record of actual usage situations and big challenges to fully comprehend the dataset.

In the case of the Vistorian network, initial logging studies started in 2017 to trace interactions [7]. The Vistorian research team has so far developed a thorough logging data collection to monitor detailed interaction events. In addition, the team developed pop-up bookmarks for annotation and a wizard to help with data generation. There were also multiple workshops and courses to teach networks with Vistorian and collect complete user logs. The growth of Vistorian logging research over a year produced a sizable dataset that necessitates further study. If properly analyzed, the logging dataset can have significant meaning. It has the potential to show usability issues, website performance, usage patterns, and learning journeys.

1.2 Motivation, research objectives

A thorough comprehension of the dataset forms the basis of an effective analysis of logging data. However, while the logging covers almost all interactions possible on the Vistorian, the analysis remains exploratory with a high-level goal: to find patterns in visual exploration.

The Vistorian's log collection, which spans more than a year and includes numerous qualitative studies, is an invaluable resource for helping us understand networks and users. This dissertation aims to visually present the logging data for analysts to see through data and to bridge the research gap between studying interaction logging theoretically and the case-specific data analysis process. We aim to offer different perspectives for analysts to look at the data in hopes of giving inspiration for further investigations into user patterns.

There are few uses for visualizing InfoVis logging data, even though dashboards can serve the dynamic needs of visually reporting data in practically all business sectors. Especially since the pandemic outbreak, we have seen a sharp increase in dashboard design cases. This thesis uses an analytical dashboard as the research focus to examine how InfoVis systems can be tailored to support analysts' exploratory analysis. Furthermore, we can unfold how analytical dashboards' creation process helps designers understand and communicate insights, which will have more general implications for dashboard users beyond this case-specific study.

1.3 Problem statement, research questions

Problem statement and usage scenario

There are few studies in reporting InfoVis log data of this time scale and complex user composition, and few examples of analytical dashboard applications for this scenario. The Vistorian user interaction logging data covers user activities in the wild over a long period. The dataset is growing as time develops, there is a lack of solution to support live updates to monitor user activity. As we have the messy data set at hand, there is an urgent need to create a visualization use case to guide analyst to understand the data comprehensively.

Our analytics dashboard solution targets **expert users**. In this case, our dashboard users are analysts who conduct evaluation research in Vistorian networks. More specifically, designer is also part of the expert user group, which is common in analytics dashboard design. Expert users know their data set and can easily build familiarities with the dashboard contents. The usage scenario for analysts calls for less requirements in instructions or visualization literacy, but high standard for the designed components precisely tailored to analytical needs.

Research questions

This dissertation intends to tackle the challenge of visualizing the logs and answer the following question: **how can we design a visualization application to report extensive session logging data that enhance analysts' understanding of user exploration structurally?**

To answer this question, this thesis intends to investigate these sub-questions:

RQ1: How to present logging data from different perspectives of the dataset?

RQ2: How to design the visualization to cover the extended temporal scope and different users?

RQ3: How to arrange the visualizations for analytical usage?

1.4 Methods, Intended contributions

In this dissertation, we present Vistorian Dashboard to answer the above research questions, an analytical dashboard reporting user interaction logs from website overview, visualization comparison, and user activity timeline.

Methods

This thesis formed research methods around task analysis sessions within the Vistorian analysts' team, engaging users and designer together to understanding the characteristics and design challenges of the logging data set. The sessions resulted in a list of tasks with priority marks from different perspectives. It provides valuable guidance in leveraging design decisions about contents and visual representations.

With the tasks list, we used data sketches and iterative design methods to improve our design while we evaluate the design with calculated log data in terms of how the design give analysts insight about the tasks. A more detailed methodology will be covered in Chapter 3.

Intended contributions

The primary contribution would be **the final design** of the analytical dashboard. The presented design structure can describe the dataset comprehensively. It accepts an integrated source format for the data used. Analysts can generate and upload the data for updated information. The dashboard allows analysts to monitor user activities, look for data abnormalities and gain insight for possible future research. During the data analysis process, **the patterns in real data** revealed by the dashboard are the secondary contribution. From the dashboard, we can see how user fluctuate during the 16 months, what do different user types prefer in using the Vistorian tool, and how they interact within their own sessions. Finally, the **design process** for this dashboard hopefully can serve as a case study for effective design in the dashboard community. We will discuss how to seek a way out of the pile of design choices, from data selection to visual representation.

1.5 Thesis outline

We intend to narrate this thesis according to the following outline:

Chapter 1 Introduction: Explain the background and necessity of this study, pose research questions, and state our intended contribution and high-level methodologies.

Chapter 2 Related works: Build this thesis on three aspects of existing literature.

Chapter 3 Methodology: Explain the logging dataset and task analysis methods to guide dashboard design.

Chapter 4 Design process: Describe the complete design journey of sketches, iterations, and all the detailed decisions to answer the research questions.

Chapter 5 Implementation: Reflect on the web dashboard implementation process with actual data and evaluate if the design reached its aim.

Chapter 6 Evaluation and discoveries: We discuss the findings about usability and data patterns after evaluation with real data set.

Chapter 7 Discussion: Reflect on where this thesis succeeded, what the limitation is, and potential future study of dashboard design.

Chapter 8 Conclusion: Shortly conclude the design outcome and research questions answered.

Chapter 2

Related work

2.1 Evaluating user interaction in visual analysis

Through decades of work, researchers in the visualization community have actively searched for a structural way to evaluate the usage of visualization systems. By visualization systems, we define those with a graphical user interface to process source data into creating a visualization. A common use of such systems is to support visual analytics, where analysts use visualization as the primary medium for data exploration [8, 9, 10].

The distinctively different initiatives of evaluation studies of these systems create a rich space of various methods and evaluation criteria. Scholar took the scenario approach in 2012 to map out the full scope of visual data representation evaluation across the design process through an extensive literature review [2]. Within seven scenarios identified, Lam et al. proposed applicable methods and data examples to support fellow researchers' workflow. They kept the categorization of high-level processes and low-level visualization actions separate. However, evaluating user experience with low-level feature specifics remains scattered information without the full picture of user intent and exploration journey. Furthermore, the scenario of evaluating visual analytics and reasoning has its limitation by its definition that stays in individual lab experiment evaluation. Thus, these under debate categorizations create vagueness and overlapping situations for learning visual analytics processes.

Interaction contributes as a critical component of information visualization systems apart from visual representation [1]. Guided by the scenario approach [2], the second thing to consider is evaluation methods and criteria, which leads to the other exploratory field. Qualitative methods have a rich theoretical basis for learning how users interact

with visualization systems like interviews, field observations [2], and the think-aloud method [11]. In the quantitative realm, while researchers agree on the value of collecting interaction history [6, 12], the rationale of the design and the analysis of such collections remain under discussion. In the journey of exploratory visual analysis, the user may or may not have a predefined goal to start [12], and they may update and refine the goals throughout the journey [8], creating difficulties to understand the semantic meaning of the quantified interaction patterns. Then, many studies which use lab experiments and explicit tasks for participants [8, 6] cannot comprehensively simulate the real-world scenario where different types of users drop out in the middle of the exploration for various reasons.

Visualization taxonomy theories help in unfolding the semantic meaning of the visual analysis process. The hierarchical structure from low-level events to high-level categories and sequences [12] makes the scatter sands of interaction data gather into meanings. Taxonomies dimensions vary from most discussed interaction techniques [13, 14, 1] to user tasks [15, 10]. For interaction taxonomies, one recognized method is to categorize by user intent; thus, researchers created broad categories of select, explore, reconfigure, encode, etc. [1]. However, the same action might represent different intents in different stages of visual analysis, which might cause trickiness of information given by this method. While another is to categorize actions based on semantic intents in the visualizations [4], where high-level categories are classified by “data change, visual change, note change, and history change.” In this method, low-level actions are specified in each category, which needs appropriation for each evaluation case. Current application of taxonomies focusses on evaluating the interaction logs and proves to be quite effective in bridging interaction data to semantic reasoning. Pohl et al. in 2012 [16] conducted a case study of two InfoVis systems to evaluate their interactivity based on user intent taxonomy. Some scholar used a novel grammar-based approach to evaluate seven taxonomies’ performance applied to one representative log dataset [3]. Others combined a set of quantitative taxonomies with qualitative research to visualize the evaluation results, demonstrating the potential of taxonomy theories in giving a clear view of user interactivity with the visual system [6].

2.2 Visualizing user interaction logs

The interaction logs of InfoVis systems prove to be a powerful quantitative tool for evaluation analysis. Logging has the advantage of automatically recording the actions and pace of the user interaction with no supervision on the side. It can capture large amounts of user data in the wild. Challenges exist throughout the exploration journey of large datasets, from their original design to reporting and analyzing results.

Current studies into logging data expand the scope of its formality from web-based clicks to more natural ways of interaction. For natural user interfaces, there is growing attention to studying logging users' spatial movement using hardware like leap-motion [17]. Systematically, scholars summarized interaction logs beyond mouse and keyboard actions into 2D touch input, 2D spatial arrangements of the device, and 3D spatial movement with the device [18]. In addition to actions performed on devices, researchers also used eye-tracking logs to study attention changes throughout exploration [6]. Although the dominant format of logs analyzed are web-based session logs [9, 3, 19], desktop application logs of commercial tools like Tableau [20, 16]. Those applications are the most widely used and support complex visual analysis tasks.

When designing logging data, Lam et al. [2] addressed the scenario approach in its benefit of realistic evaluation of actual field data. Most structured analyses start with a clear goal and evaluation criteria. When designing the interaction logs, analysts do not have a clear picture of how to calculate the log data or what analysis will be performed, making the analysis rather exploratory [8]. This leads to the next question, what kind of data to collect? For those cases with a small dataset, either in a laboratory experiment with limited users [3] or with a clear design plan [9], analysts have a clear picture of data needed. While for more exploratory visual analysis, researchers have to explore for hints and leads among large datasets. Without careful design to balance low-level actions and feature-specific tasks, the logging may contain much noise, making the analysis more challenging (Vuillemot et al., 2016).

A primary usage for logging data in InfoVis systems is to study user interaction, from low-level interaction to high-level cognitive patterns [21]. Existing research diverts in terms of audience for the logging data. For those analysts who study other users' actions, there are studies solely recording and reporting interaction histories [17], while most other studies are dedicated to discovering users' reasoning patterns [8, 22]. For those who study visualization taxonomy, logging data are used to develop taxonomy theories [13] and test theories' rationality and applicability [3]. Another common usage

is to use the analysts' logging to assist their sense-making process, Some scholars [20] introduced a blocked graphical history module in Tableau in 2008, and others [19] presented a similar browser extension in 2016.

The community used various visualizations to report and present these logging data. Many designed applications with multiple views to depict logging data from different angles [19, 17]. As time played a crucial factor in logs, many scholars used temporal data as the dominant consideration in their visualizations. Heer et al. [20] emphasized slices of graphical history, sorting miniature charts by time stamps. Paluka and Collins [17] recorded spatial movement with a time slider to show the changes. Nguyen et al. [19] presented a block timeline for segments of actions on different pages. For logging data visualizations without time information, researchers used heatmaps for data coverage [6, 23], tree maps, and networks to visualize the exploration pattern of individual users [8, 6, 19]. Many publications also integrated box plots, bar charts, and diversity distributions to report categorical logging data [8, 3]. Collectively, interaction logs aggregation holds rich information about different user types and their exploration journeys. The potential of interaction logs is not only to find a pattern for visual analytics but also to measure user experience quantitatively. Therefore, showing the interaction logs' full picture is a starting point for further task analysis.

2.3 Dashboard design potential

Dashboards are widely used to large aggregate amounts of data in multiple views. Although there is no strict definition of dashboards, we can still grasp its essence through Wexler explanation: "a visual display of data used to monitor conditions and facilitate understanding" [24]. As its applications developed in the past decade, dashboards gained attention in the research community, and scholars expanded the discussion to a broader landscape as a distinctive type of data visualization.

To understand dashboards' inclusive potential, Sarikaya et al. [25] gave a comprehensive survey in 2019 and categorized dashboards by purposes: those for decision support and those for communication and learning. For every dashboard, several design considerations are listed from the aspect of the intended audience [25]. Bach et al. [26] expanded the design space of dashboards in 2023, identifying design patterns from the contents of data, metadata, and visual representations to compositions of layout, screen space, structure, interactions, and color encodings, covering most components in dashboard design. Those guiding papers offer a comprehensive understanding of the

possible design decisions for this paper's dashboard.

Dashboard applications are ubiquitous in both industry settings and academic communities. They exist in almost all domains covering business, and public sectors. In business intelligence, design cases vary according to specific needs, while researchers focus more on how to make effective content decisions [27, 21]. For the increasingly heated field of learning analytics, analysts follow structural LAD classifications to guide their design [28]. Others use dashboards as a combination of user research materials and design objectives to guide decision-making [29, 30]. Health management witnessed more prevalent usage of dashboards to monitor patients [31, 32] improve care, and report trends in pandemics [33, 34], etc.

For most use cases, user-centered design approaches are adopted to guide design decisions of dashboards [35, 29]. Through user research sessions, researchers identify tasks worth attention to and sort out priorities to structure their dashboard and iterate through user evaluations. To design effective dashboards, researchers studied how to maintain visual consistency [36], and employed AI-driven methods and automation to generate dashboards [34, 37]. In addition to design guidance in visualization theory, scholars also discuss different strategies to make choices through decision models to support effective design [27].

Dashboards prove their flexibility and adaptivity in reporting large datasets in many interdisciplinary fields [35, 37, 38]. However, there are few cases of using dashboards to report users' logging data, and there is a lack of discussion of the potential of dashboards in these scenarios. While previous sections discussed multiple data analysis challenges in interaction logs, most visual representations reflect limited angles of the data set and only partial information. Dashboards have the intrinsic advantage of reporting and presenting large data sets at users' first sight, offering possible appropriation in logging data evaluation, and linking multiple visualizations together to guide further analysis decisions.

Chapter 3

Methodology

This thesis employs a task analysis approach to handle the design challenges posed by complicated datasets. To structure the complete task analysis, we split the tasks into three aspects: 1) understand the context through listing the intrinsic features of collected logs, 2) understand user needs of dashboard components through discussion sessions, 3) give an overview of the whole iterative design process.

3.1 The Vistorian Dataset

The anonymous interaction tracking technique has been operational for over 16 months as of July 2022, generating extensive meta-data for over 730 user sessions. In the meantime, qualitative studies conducted in tandem with the logging period increased the complexity of data collected. Tasks analysis here is meant to clarify the core characteristics of the dataset. We summarized the complexity as follows.

The comprehensiveness of event list: The Vistorian logging consists of overall seven categories of 94 atomic events. Each event log has the information of user id, session id, start time, and end time. For each category, analysts grouped the events into 16 operational level classes. The categories encompass almost all features provided by the Vistorian tool:

- Data Management related to creating networks,
- Visualization and Interaction related to visual analysis,
- Help resources,
- Interests and communication,

- Bookmarking tool for annotations and feedback,
- Errors reported,
- Other logs related to user activities.

A mixture of analyst groups: As Vistorian logs are anonymous and collected in the wild, they contain various user types. Current research has identified four categories of analysts based on the primary network-building steps:

- Demo users: They mostly use help resources to play with demos and do not upload any data;
- Data strugglers: They reach the stage of uploading data but meet barriers to successfully generating any networks;
- Single session explorer: They only pay one visit to Vistorian and never return;
- Multiple session explorer: They succeed in generating at least one network and pay multiple visits to explore their visualization.

Volatility of data distribution: Alongside the 16 months of tracing user interaction, analysts ran multiple workshops and courses to guide users in learning network visualization and identifying barriers in visual network exploration. These variables can cause fluctuations in user activity. For instance, it might affect user type composition, user session time, and their preference for interactive techniques. Alternatively, appropriate representations of these data may reveal unexpected insights in comparison to other time periods.

3.2 Task analysis sessions

After a preliminary understanding of the dataset challenges, we focus on the information worthy of being presented on the analytics dashboard. Guided by the evaluation framework proposed by Lam et al.[2] in their 2012 publication, we discussed the top-level scenario and goals, based on which we conducted three task analysis sessions in mid-June to obtain the low-level tasks questions for dashboard design.

Scenario: The primary audience for this dashboard is also the designers and analysts of the log dataset. The collected data evaluate how users interact with Vistorian networks, falling into the general scenario category of evaluating visual data analysis

and reasoning [2]. Because we have little information from anonymous logs about user intents and extensive knowledge about distinct user types, we may describe our scenario as evaluating user visual data analysis pattern and performance.

Goals: Under the given scenarios, branched goals help us establish starting points to sketch out the dashboard so that we can sort out possible data components according to the analytical needs of the intended audience. During open discussions with Vistorian researchers, we came up with three goals covering different angles:

- **Overview (G1):** Understand the general user performance of the Vistorian through the entire tracking period.
- **Focus on visualizations (G2):** Identify interactivity patterns for each network visualization.
- **Focus on users (G3):** See users' visual exploration journey and identify patterns.

Task generative sessions: For each listed goal, there can be a set of sub-tasks directing to specific questions users are interested in. To obtain this task list, we organized three generative sessions with Vistorian analysts first to brainstorm possible information we can get from the dataset and then shortlist the priorities to be presented in the dashboard. The table at the end of the chapter shows the three-level task taxonomies (see Table 3.1).

3.3 Iterative dashboard design

The log data is a mist of scattered information, while the task analysis sessions at the beginning serve as guidance flashlights and remain highly exploratory. We adopted the iterative design method to revisit constantly listed tasks and test our design with analysts. The following chart visualizes our overall design process, where we roughly followed the framework of planning - designing - implementing - evaluation, and inserted evaluation and testing in the design and implementation stages multiple times to refine the dashboard (see Figure 3.1).

In the planning stage, we sketched the first draft to interpret the data from our point of view. After discussing task analysis, we utilized data sketches with a mind map to generate feasible structures across pages and arrangements within pages where dashboard design patterns [26] clarify and facilitate key design considerations to guide

non-experts. Then we constructed a complete dashboard design while validating our design decisions with analysts. For implementation, we designed the data format imported to charts using a dummy dataset, and made a working interactive prototype with the test data. Finally, we evaluate every design component with the real data set organized by Vistorian analysts. While, to some extent, the design stages overlap with each other, it is the communication process within the team that pushes our understanding of both data itself and design choices, making it all possible in the time constraints.

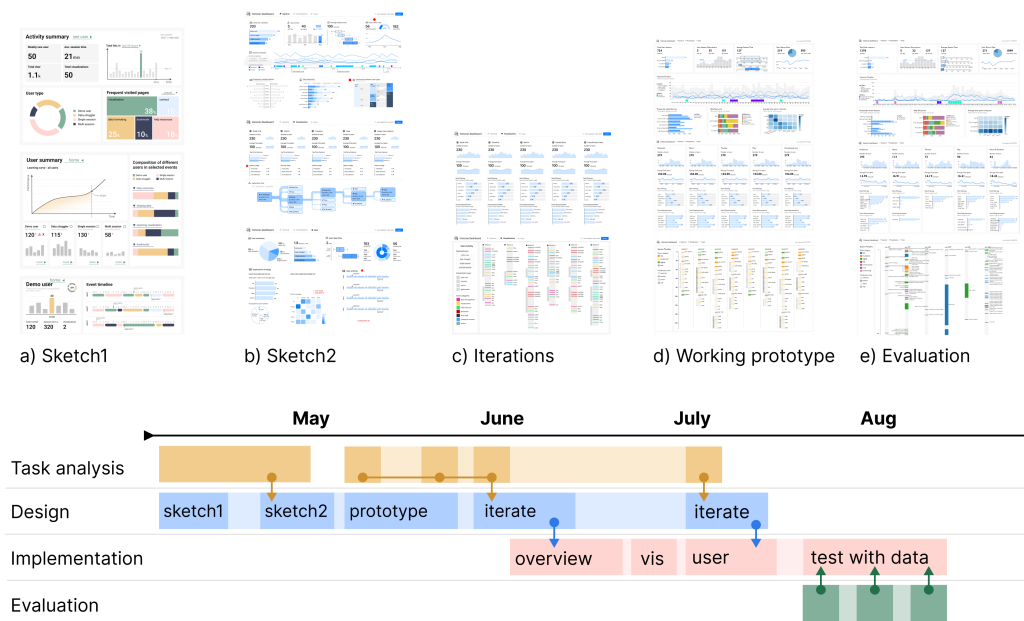


Figure 3.1: Design process of Vistorian Dashboard: Images on the top marks the output of four iterated versions in Vistorian dashboard design, including two initial design sketches a) and b), iterated versions in c), implementation of prototypes in d), and evaluation with real data in e). The Gantt chart below describes the timeline of four phases design process which influence each other.

| <i>Scenario:</i> | |
|---|----------|
| <i>Evaluating user visual data analysis pattern and performance</i> | |
| <i>G1: Overview</i> | Priority |
| 1 What is the current number of total users? | * |
| 2 What is the trend of user visits changing over time? | * |
| 3 What is the user session length distribution for different user types? | * |
| 4 How many users return after one visit? | * |
| 5 How do user visits change with the events? | ** |
| 6 What are the most frequently visited features? | * |
| 7 How does the demand for help resources vary? | * |
| 8 What are the popularities for different bookmarks? | / |
| <i>G2: Focus on Visualization</i> | Priority |
| 1 How many visualizations are used together in an individual session? | / |
| 2 How much time do users spend on each visualization? | * |
| 3 What is the number of users per visualization? | * |
| 4 What are the paths users follow to explore the visualizations? | / |
| 5 What are the most popular interactive features for each visualization? | ** |
| <i>G2: Focus on User Patterns</i> | Priority |
| 1 What is the user exploration strategy in choosing visualizations? | * |
| 2 What are the interaction patterns for individual user sessions? | ** |
| 3 How many data files do different users' upload? | / |
| 4 What is the combination of visualization choices for those who explore multiple sessions? | / |
| 5 What is the general visual exploration sequence for different types of users? | * |

Table 3.1: Task analysis results: A task list covering the top-level scenario and three goals from 1-overview, 2-visualization, 3-user patterns, followed by detailed tasks with priority labels. **: high priority, *: medium, /: low priority.

Chapter 4

Vistorian Dashboard

This chapter describes the final designs for each component of the Vistorian dashboard (see Figure 4.1). We will elaborate on design decisions, information encodings, and design tradeoffs under the constraints of limited dashboard space and project duration.

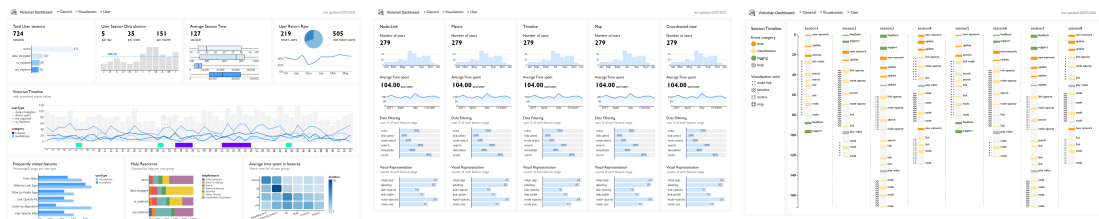


Figure 4.1: Working prototype of final design for Vistorian Dashboard: General overview (left); Visualization comparison (middle); User session timeline (right).

4.1 Page compositions

For each dashboard, designers need to consider two aspects: content patterns and composition patterns [26]. We build the Vistorian dashboard on task analysis results discussed in chapter three and start by deciding on high-level dashboard compositions as is shown in Figure 4.2. These discussed compositions organized different perspectives of the dashboard and set principles to maintain clarity and consistency.

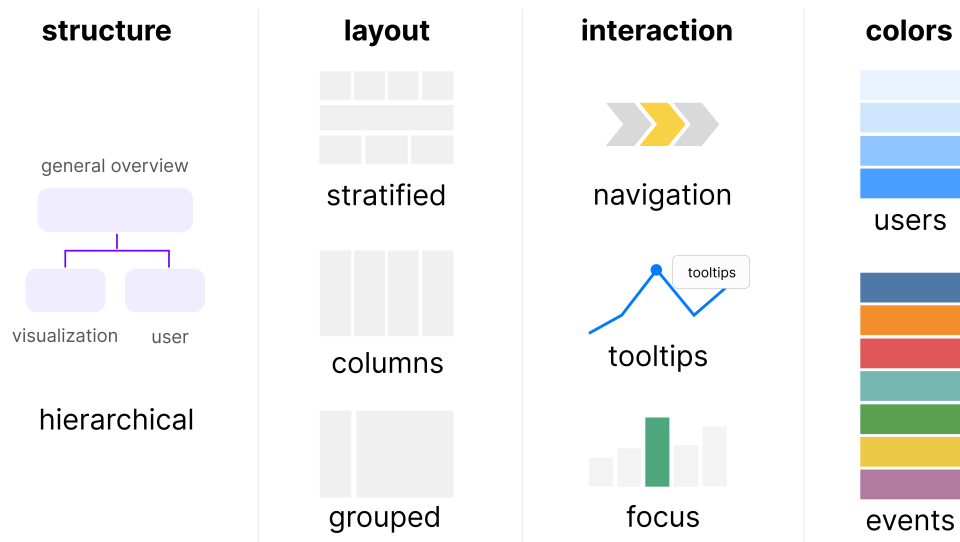


Figure 4.2: Vistorian Dashboard page compositions including three-page hierarchical structure, each page's layout, interaction methods, and color encoding rules.

Page structure and layout: The three main task goals covering overview statistics, visualization comparison and user activities determine that multiple page structure is the suitable choice here. Here we adopted a mix of hierarchical with parallel structures. The **General overview (G1)** is the leading page, followed by two parallel pages **focusing on visualization (G2)** and **focusing on users (G3)**. As we have settled on a rather complex page structure allowing a certain depth in data representation, a screen-fit screen space can save users' time scrolling over charts to keep information clarity. On each page, the layout differs according to the semantic needs of the listed tasks. Page overview adopts a stratified layout, page visualization uses a table layout, and page user employs grouped layout.

Interactivity: In terms of interaction, we provide straightforward navigation and limited exploration options. To move between pages, we used a sticky top navigation bar containing the dashboard title, a list of buttons directing each page, and a timestamp of the latest update. There exists a tradeoff between interactivity and visual encodings for data exploration options. Overall, the Vistorian dashboard insists on providing focus to specific data while limiting data filtering options to prevent interference with the bigger picture.

Color encodings: Multiple pages design naturally leads to high demand for consistency across all charts. There are two types of common color schemes in Vistorian Dashboard, corresponding to two dataset features explained in Chapter 3.1.

(1) To tackle the challenge of a complex collection of event categories, we use distinctively different colors to represent different events. In specific charts, the color selection differs according to the size of the chosen sub-collection.

(2) For the mixture of analyst groups, four different colors are originally selected in the first version sketches. However, when combined with events, these hues are difficult to differentiate. Moreover, the semantic meaning of analyst groups indicates how advanced they use the tool. Therefore, a set of blue shadings is used where lighter colors represent demo users and data strugglers, and darker colors represent single-session and multi-session users.

4.2 Page: General overview

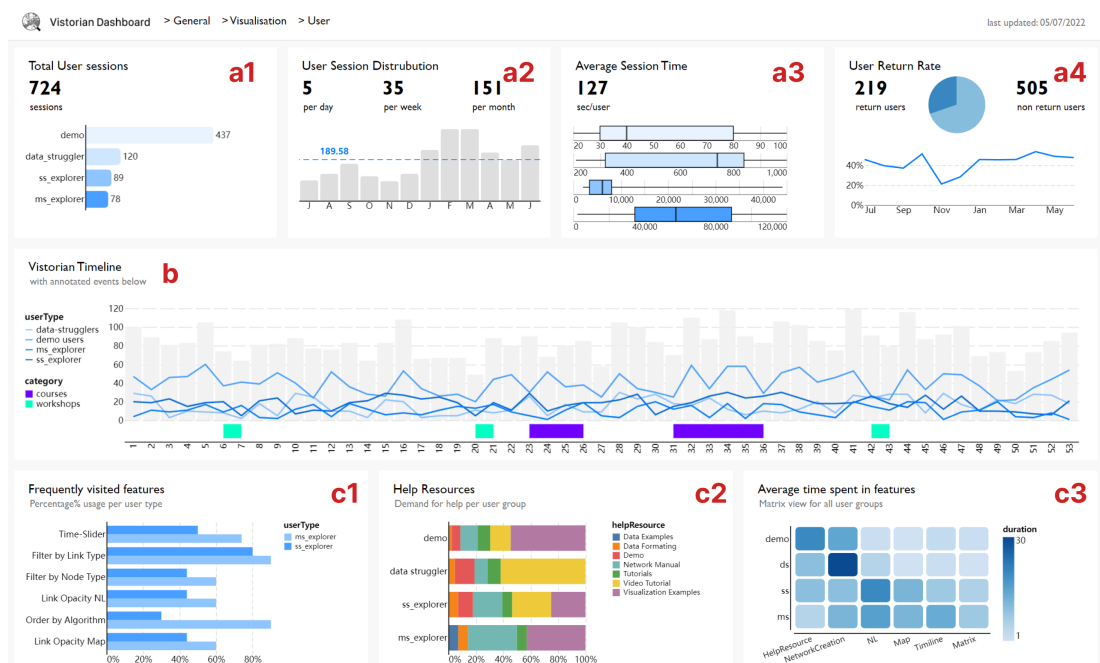


Figure 4.3: Final design (prototype) in page general: A navigation bar on top, three stratified rows with each block marked reference number in red, including a1) total user sessions, a2) user session distribution, a3) average session time, a) user return rate, b) Vistorian timeline, c1) frequently visited features, c2) help resource, and c3) average time spent.

The general page is responsible for reporting overall trends of the Vistorian activities across 16 months of data, including user statistics, temporal trends, and key feature usage. The tasks listed for the general page cover diverse topics and data from multiple angles. Therefore, the design rationale in the general page focuses on the arrangement

of each block.

The stratified layout on this page aims to organize three levels of information, describing (a) who paid visits to the Vistorian and how long they stayed; (b) what happened to the Vistorian, and (c) what did analysts do using the Vistorian (see Figure 4.3). Thus, the general page forms the start of the Vistorian user story and provides a research background of usage trends.

Total user distribution (a1): This block answers post in G1.1 (see Table 3.1), “what is the current number of total users?”. Using the number of total users as a critical performance indicator to address the question, this section also includes a basic bar chart that illustrates the composition of all users. This bar chart is crucial because it sets the tone and introduces four analyst groups at the start, which many charts use as a legend. As we can see from the results, demo users take the lead, and the other three groups are far fewer.

User session distribution (a2): Adding the temporal dimension to user numbers, we landed on the design of the second block. Task G1.2 (see Table 3.1) demands the trends of users per day/ week/ month. Here we have the monthly data and calculate KPIs accordingly. The monthly distribution bar chart takes the latest 12 months into account. A rule is added as a threshold to highlight the average user number, and detailed monthly data are masked in tooltips. If a user wants to focus on a particular month, he or she can move the mouse on the bars to see tooltips.

Average session time (a3): For task G1.3 (see Table 3.1) addressing session length distribution, the analysts want to know the distribution of user session time. Therefore, we listed the overall average session time as KPI on top. Data collected in the wild can easily have extreme data points, making the mean value not a very good representation of data characteristics. In detailed charts, each box plot represents one type of user, reporting the quartile statistics. Another modification during the prototype implementation was to facet different users and adjust the duration scales because of the significant difference to keep clarity of each plot.

User return rate (a4): The last block in the first row provides extra information on how many users will return after one visit, as indicated in G1.4 (see Table 3.1). The pie chart depicts the proportion of returners and non-returners, whereas the return rate line chart displays the total number of users and the percentage of returners. Users in the wild can have multiple reasons to stay or leave. The visualizations presented here do not imply good or negative, but rather could serve as conversation starters for further research into why people leave and what causes a sudden change in the rate at a given

period.

Vistorian timeline (b): The middle row contains the yearly Vistorian timeline. Task G1.5 (see Table 3.1) is considered a priority from a Vistorian analyst's point of view, which asks the question of how do user visits change with events; hence, we consider it the center of attention on this page.

To visualize how user visits change over time, we need to sort out several layers of data. The analyst's data used here contains more details than the a2 miniature chart (see Figure 4.3). We used weeks as a time unit and sorted out numbers for four groups, so there are over 50 bars taking up the entire year. When sketching this chart, we considered four lines against the light grey bar of the total number that can simultaneously highlight the user groups and provide extensive background information. Below the main component is a swim lane of events annotated. The events consist of qualitative studies, tool feature updates, short-term workshops, long-term courses, and publications. Each event is marked by starting time and ending time. Specifically for user-engaged activities, there is also information about the number of attendees. Events are color coded as categorical data to distinguish with user types.

This view attempts to provide analysts with a richer knowledge of user trends by allowing them to consider events as factors influencing the number of user types.

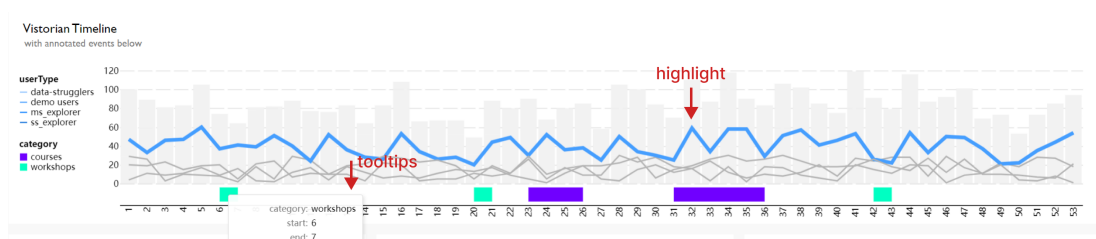


Figure 4.4: Interactivity in b) Vistorian Timeline prototype: when clicked on lines, it shows a focus view; when the mouse hovers over each point or event, it shows tooltips of complimentary information.

However, the mix of four lines still causes visual burden. We introduced interactive features as shown in Figure 4.4 that support shifting focus according to the analyst's needs. First, the timeline includes a set of tooltips on lines, bars, and events to reveal detailed statistics. In addition, clicking on one user line adds stroke width to place emphasis, while clicking on other lines causes them to fade to light grey, signifying less emphasis. At this point, it becomes easier for analysts to see the trends. The timeline view not only answers the prioritized charts but also use interaction to report data clearly and efficiently.

Frequently visited features (c1): Of all Vistorian features, what are popular ones among users is another question analysts want to know (see Table 3.1). This block had several modifications before settling on the current grouped bar chart. If the block includes every feature and user type, it will lead to chaos and loss of focus. Therefore, we focused on more advanced single-session and multi-session users because they spend more time exploring networks from their own data sets. The listed features on the y-axis are also selected and ranked by order of analysts' needs. The width of the bars indicates how much percentage of this user type used this feature.

Help resources popularity (c2): This block addresses task G1.7 (see Table 3.1), reporting users' varied demand for help resources (see Figure 4.5). As the networks require advanced visualization literacy, help features are essential in guiding users to create networks. There are two perspectives to consider help resources. One is to see the composition of user types within each resource's usage; another is to see the popularity of different resources within each user type.

Initially, we started using the exact numbers of each resource's usage shown in Figure 4.5 part 1 and found out "visualization examples" are used significantly more than other features, while demo users contribute to the majority usage of every feature. As we reflect on this chart, too much information in one chart causes ineffective representation. Finally, we choose the second perspective, using percentage usage to demonstrate what resources are more popular for each user type, as we can uncover more insights regarding different user groups' preferred actions.

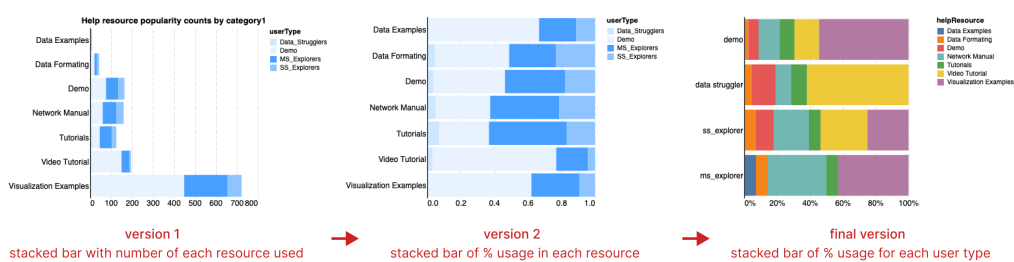


Figure 4.5: Iteration process of help resources: version 1 shows the exact aggregated number of each feature logs, version 2 shows stacked bars of percentage usage for different user type in each help resource, the final version shows stacked bars of percentage usage for different help features in each user type.

Average time spent in features (c3): The last block view in the bottom row changed as we understood the data more deeply. In the first few sketches (see Figure 4.6), we want to show the user conversion using a Sankey diagram, indicating how demo users

become multi-session users or where they leave the tool in the middle. However, this picture is not entirely accurate because some users begin as multi-session users, while others do not adhere to the journey as we perceive it.

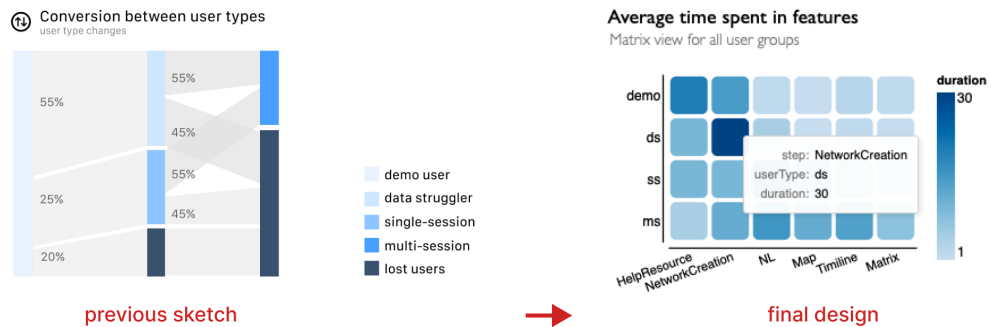


Figure 4.6: Iteration process of user exploration matrix: the previous sketch was about user conversion; the final decision is a heat map of average time spent in different features for four user groups.

After two discussions with analysts, we decided to shift our focus to depicting user journeys by segmenting their duration in stages of exploration. We agreed on a matrix view. Y axis is sorted by user types, from demo to multi-session users. Because we have limited space for this chart, we must weigh the level of abstraction against available space. We organized the X axis by main pages in Vistorian: help resources, data creation to four views of network visualizations. The shadings of each square encode the time spent in each step. In the matrix, each row shows where the users spent the least and most time.

4.3 Page Visualization

In the page structure hierarchy, the general page takes the lead, and the visualization page follows. While the general page arrangement may share similar parameters with other web tracking dashboards, the visualization page is more tailored to the Vistorian InfoVis application. The dynamics of temporal brushing features and multivariate network format make the visual exploration in the Vistorian distinctively unique (see Figure 4.7). The interface of four visualization views shares the layout of main networks in the center with a left side column of interaction choices and the top bar of filtering or sliding choices. The four visualizations also support free selection and explorations.

Such interface, as the creator puts it, "can allow for exploration, enable serendipitous discoveries, and serve as a mental metaphor to help us remember and reason about the data" [39]. User interaction logs are then aimed at uncovering the discovery process and patterns, especially for this visualization page.



Figure 4.7: Visualization exploration pages in Vistorian including a node-link diagram, timeline diagram, matrix diagram and map diagram (from left to right).

When sorting out the tasks from task analysis sessions, we discovered there can be two categories of tasks. Analysts are interested in the popularity of different views and interactive features. They raised questions like "What percentage of users used x features" or "how long do they spend in x visualization." They are also curious about all users' generalized patterns and strategies in their exploration journey.

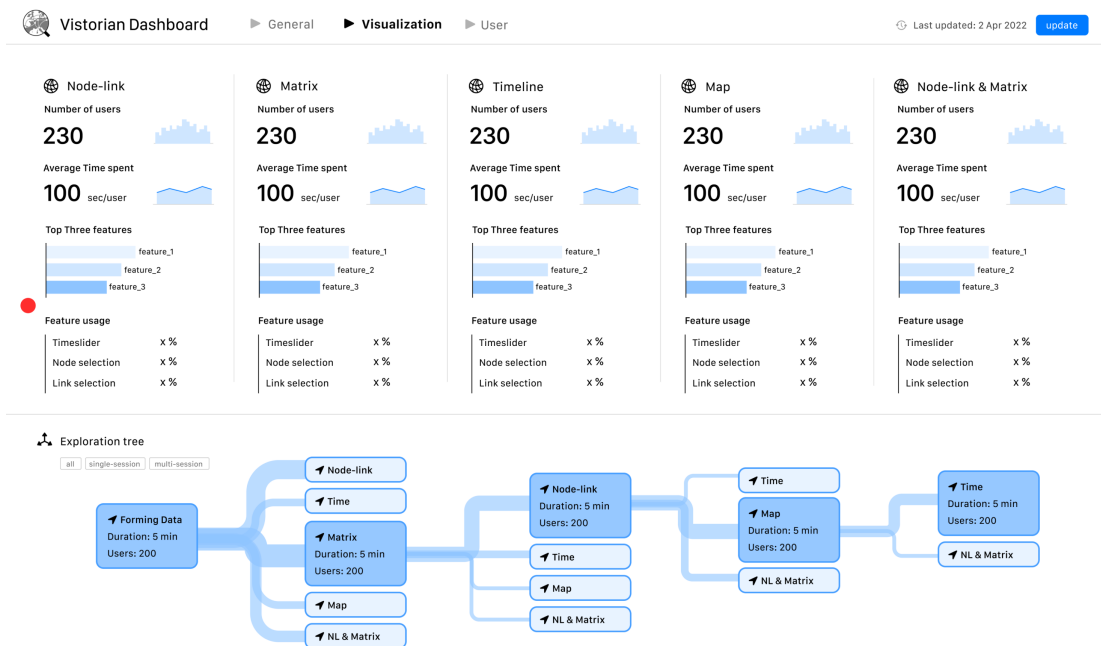


Figure 4.8: Visualization page preliminary sketch version: visualization comparison columns on the top row; below is a exploration tree depicting user journeys.

Through the iteration process for the prototype, we started by including both discussed perspectives on the single page shown in Figure 4.8, the top row being comparison columns for each visualization view and the bottom row representing the general exploration tree filtered by user types. After a round of evaluation, we revisited the design and tasks. While the exploration tree has the same issue as the user conversion diagram in that generalized data causes information loss, it also requires scientific research into how to generalize its patterns. The limited screen space may not support such a complex diagram and takes away much space on the top row. Instead, the main goal of this dashboard is to let log analysts see the complete data directly and visually. As a result, we deprioritized the exploration tree and expanded the visualization comparison to the entire screen space.

The final visualization page design split the screen space into five columns. Each column represents one visualization view (see Figure 4.9). Overall, the user can regard this page as a big table where the top row is five view names: node-link, timeline, map, matrix, and coordinated view, and each row below represents different dimensions of logging interpretations of analyzed tasks. This page layout establishes a sense of concise order and, in the meantime, facilitates users in comparing different views' performance metrics.

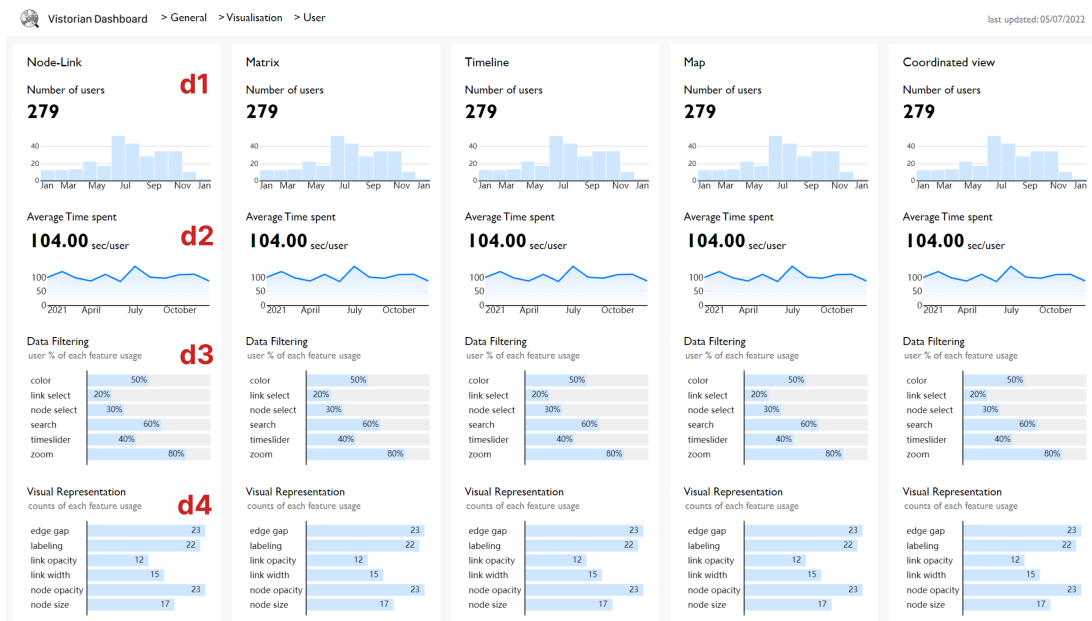


Figure 4.9: Final design (prototype) for visualization page: a five-column view covering four diagrams and a coordinated view of matrix and node-link. Components are marked in red, d1) number of users, d2) average duration, d3) interactions regarding data filtering, d4) interactions regarding visual representation.

Each view column contains visualized data of four aspects, which adds up to twenty charts on one page. Not many users reach the stage of visual analysis, mostly single-session and multi-session users. Furthermore, this page focuses on visualizations rather than users, so there is no pressing need to include four types of users that will cause information overload.

It starts by introducing **the total user number (d1)** as KPI in this visualization view, followed by a bar chart presenting the monthly distribution in a yearly scope (see Figure 4.9). When focused individually, this block helps analysts understand task G3.1 (see Table 3.1), which is how many users used this particular visualization. When analysts cast their perspectives across these columns, the five charts combined offer a critical understanding of which view is popular and do they share similar trends in user numbers over the year. Any anomalies in the numbers or trends can lead to targeted data analysis in the future.

The second block of **average time spent (d2)** shares a similar usage as the first one (see Figure 4.9). The KPI metric here is the average time spent of all time in the unit of minutes per user. The chart below uses the same time unit and scope of the latest year to depict the trends in the duration of visualization usage. The data presented here only

includes sessions in which the visualization was explored for longer than one minute. Some users construct the network but scarcely explore it, according to qualitative study findings, while others utilize these interactive aspects and spend more time. We may compare the views horizontally to determine which is more prevalent.

Before the final version, we only used a subset of features that analysts mentioned in tasks analysis sessions (see Figure 4.8). After further discussion, we decided to show all the interactive features comprehensively (see Figure 4.9), where each view has approximately ten options. To list them all, we need a logical arrangement. In the case of the Vistorian, records are collected in the wild, therefore it is impossible to determine the precise user intentions behind each encounter. Thus, we resort to the taxonomy of intents on visualization developed by Gotz and Wen in 2009 [4] and made modifications based on the Vistorian features. The first group of interaction events consists of those that can have **data filtering (d3)** effects. A typical example would be the time slider which let users brush through desired period of data. The other group of interactions is the ones that only change the **visual representation (d4)** of the visualization elements. By changing the visual aspects, users can shift focus to their preference without filtering data. For instance, we can maximize the node size and slide down the link opacity to focus on node patterns like clusters in the node-link view. To report usage of these events, we also tested with two possible data formats, one from the percentage usage of all users in this visualization and the other is the number of triggered event logs in the bar chart. We will use the real data to determine which representation is more accurate.

4.4 Page User

A collection of individual user session timelines made up the user page's final design (see Figure 4.12). When going through the list of tasks in Goal 3 (see Table 3.1), we realize there are still many topics worth exploring on this page. We could show visualization strategies from the user perspective by categorizing their choice in networks in Figure 4.10. For those who only used one diagram, a bar chart can show which one is more popular, while a matrix view can describe what combination users choose in visual analysis for multiple diagrams. Another task points to the average number of data files users upload through multiple sessions. For this, we can use a box plot and sunburst chart together to report the distribution of data files and the composition of user types, shown in Figure 4.11. Lastly, the individual user session timeline can visualize each session in swim lane views to show user patterns.

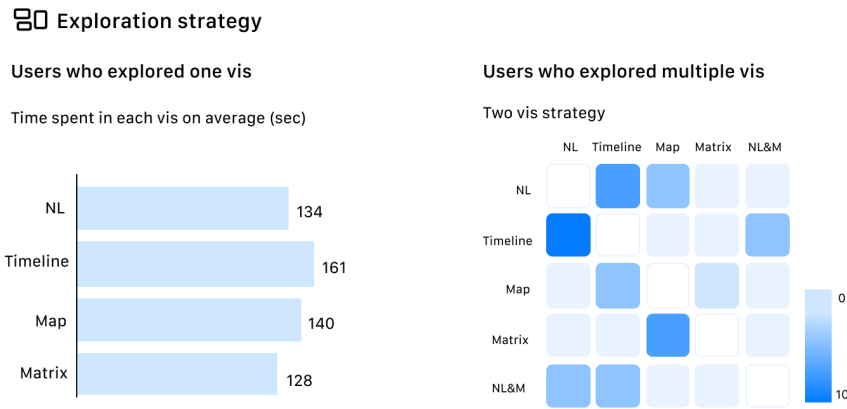


Figure 4.10: User page preliminary sketches for exploration strategy blocks including exploration duration for users who explored one visualization and matrix duration for users used two visualizations.

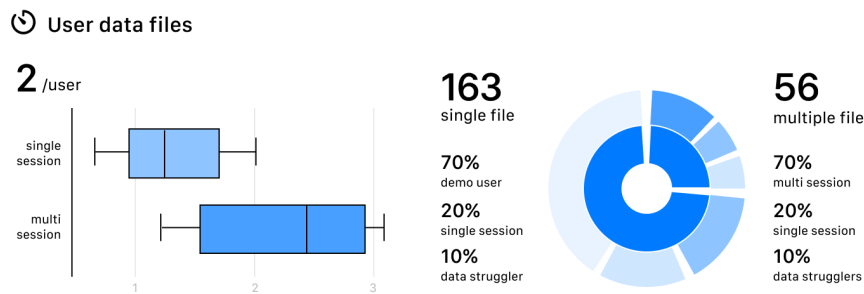


Figure 4.11: User page preliminary sketches for data file blocks including box plot of file number distribution for single and multi session users, and user composition for single data files and multiple data files.

We had another session within the team to evaluate what should be prioritized in the dashboard. As our discussion progressed about the potential of the session timeline, it goes without saying that we should prioritize this timeline view and deprioritize others. When we design the timeline view to the fullest, it can also answer the question of other tasks like visualization strategies. Logs in one session can be grouped according to event categories introduced in chapter 3, or they can be grouped into network types.

The design of this page (see Figure 4.12) focuses on (1) how to put multiple timelines in limited screen space and (2) how to color code the complex user types, visualization views, and event lists. In the prototype, we segment the page into two views; the sidebar on the right shows the view title, legends, and integrated interactive features. The majority of the screen is used to show user timelines. Right now, we estimate the

viewport can contain about eight swim lanes. The X-axis on the top organizes session numbers, whereas the Y-axis on the right measures session time in seconds.

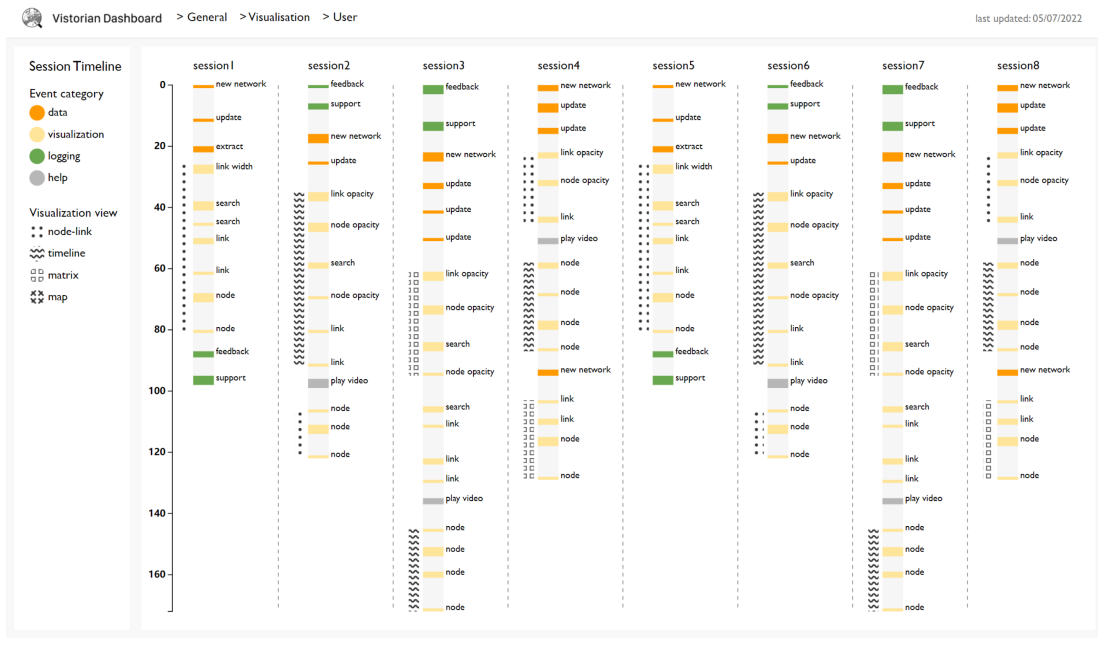


Figure 4.12: Final design (prototype) for user page: column on the left showing graph title and legends for views and event categories, main component showing swim lanes of visualized user sessions.

Each swim lane is one exploration session containing several layers of information. The grey background layer measures the entire session length, becoming the basis and reference scale for all annotated events and views. On top of the background, every single bar marks the logged event layer. The logged data supports the start and end times of each event triggered. The exploration logs mostly happen frequently with a quick click of the mouse. We anticipate the results shown in the session time, like clusters of small dashes marking different logs. From the anatomy of the logs in chapter 3, we understand there are over 90 types of events in seven big categories. It is unlikely that we use different colors for every single event.

Therefore, we adopted color legend in the prototype encoding the seven categories. This method can potentially allow analysts to identify patterns in explorations. To distinguish single events, we list the event names on the left side of the bar for detailed information. Finally, for those logs triggered in the process of visualization views, we add an extra layer of bars indicating which view the user is currently exploring. The views are not logged events but act as a grouping function in addition to the events. We also need a different set of coding for the views. Instead of filling in colors, using

mono-color textures could be a solution to distinguish them from event categories colors. The selected textures match the affordance of each diagram, for instance, we use dots to represent node-links, squares to represent matrix, arcs to represent timeline, and crosses to represent maps (see Figure 4.12).

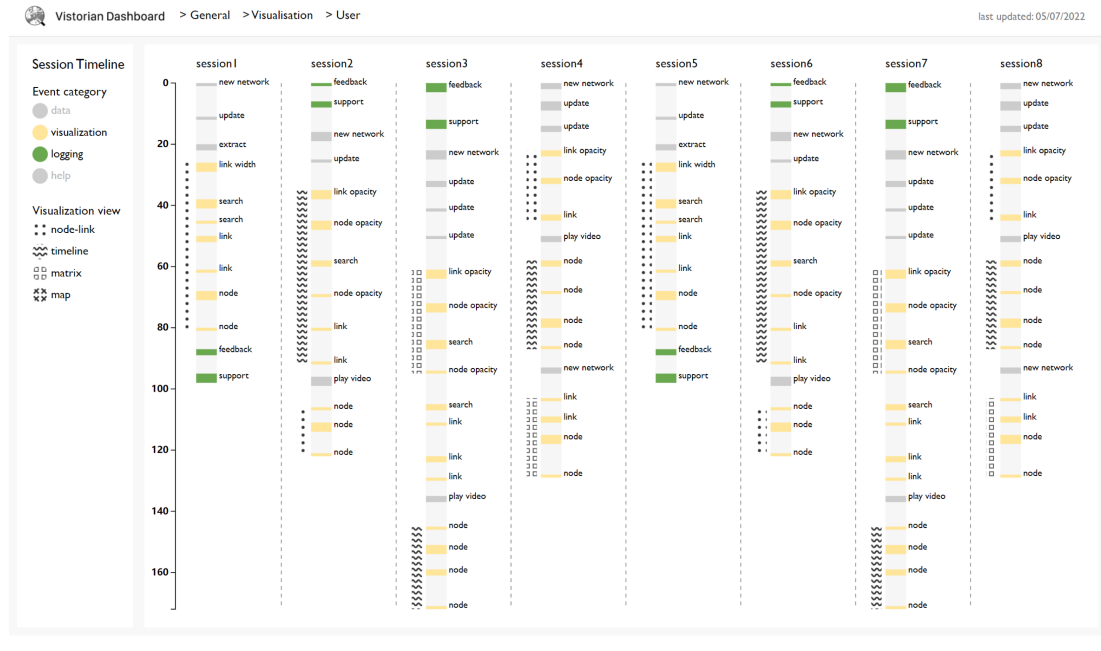


Figure 4.13: Prototype's interaction for user session timeline: when clicked on the color legend for event categories, the events in timeline will be highlighted accordingly.

The interactive features designed in the user timeline page enhance analysts' experience in seeing a more extensive data sample and identifying patterns in user actions. We provide interactive legends to help analysts focus on event categories. When clicking the color box in legends, the other categories fade to the background while only selected categories to remain their original color (see Figure 4.13). A sharp contrast between foreground and background color enables users to see the density of selected events and patterns of their occurrence. This interaction technique also corresponds with the annotated timeline on the general page, facilitating the process of creating familiarity and keeping consistency across pages of the dashboard.

The results displayed clearly what happens in user explorations. It is direct, concise, and rich in interactivity. The user page and visualization page combined marks two sub-branches of the Vistorian dashboard.

Chapter 5

Implementation

The Vistorian dashboard is an interactive web-based dashboard with multiple pages created using the Vega-lite chart library and d3.js. The source data are in the form of JSON files hosted on server. This chapter examines the selection of a tool to deploy the dashboard, the organized data sheets, the advantages, and disadvantages of using these tools, and the lessons learnt from this iterative process.

5.1 Skeleton in html

We need to launch the dashboard on web pages for easy access, customized interfaces, as well as easy updates for expert users. For that reason, we compare dashboard software and libraries to choose our implementation method.

As many business sectors rely on dashboards to make business intelligent decisions and support data analysis, there is a dozen dashboard software that can read large data sheets and produce a set of charts on demand. Dominant software includes Microsoft Power BI, Tableau, Domo, etc. However, the prototype of the Vistorian Dashboard has a very high demand for customized visualizations for analytical needs. For instance, we have specific color encodings for each user type; we have many annotations on top of essential charts combination; we have designed customized timelines that cannot fall into standard BI dashboard's visualization examples.

Therefore, we shift our attention from dashboard software to visualization libraries and web development. We decided to deploy the flexibility of website grids as page layouts and use CSS as a style guide to organize formality. From our high-fidelity data sketches, we were able to construct a nice and clean interface that placed emphasis solely on the displayed visualizations. These become the skeleton of the Vistorian

dashboard. Next, we need to choose the grammar to build our interactive charts.

5.2 Building blocks in Vega-lite

The general page and visualization pages design mainly consist of variant forms of standard visualizations. We need an easy-to-use, high-level grammar that allows flexible customization and interactive features. Vega-lite becomes the suitable choice, which uses a set of JSON forms high-level specifications to build every chart [40]. By modifying the parameters, we are able to tailor our diagrams.

Firstly, we choose the type of “marks” that suits each block’s design and refer to the chart’s library for standard data formats. The rich examples helped us build a working demo data set. We also have many key performance indicators in the first two pages’ design. These indicators are built on the calculation of data sources and are fetched on web pages using JavaScript. After forming the data structure, we added layers of additional bars, rule indicators, text labels, to match the original design. Then, we worked on visual representations of these charts, reformatting the axis, domains, and color legends to complete the block. Finally, tooltips and interactive features are implemented also using Vega grammars. Once we have the finalized charts, we can use Vega embed to insert them in the dashboard skeleton and resize them according to the screen space.

Throughout the process, there are over 25 charts built in Vega-lite. We tried out most features and summarized the pros and cons of using Vega-lite for dashboard purposes.

Vega-lite provides detailed documents explaining how it works, including a rich example library to support specification documents that beginners do not need to start building visualizations from scratch. It is of high readability and very friendly to non-experts. Also, the online editor helps designers to debug and preview the results quite rapidly. When we iterate over multiple possibilities for one block, for example, the help resources (b2) in the public page, generating different versions for preview is very convenient. More importantly, compared with dashboard software it shows much more flexibility in customizing every visual aspect with minimal effort.

On the other hand, there are also inconveniences. Because of the limitation of its development, we use separate files for each block to import data links. Consequently, when there is a need to change certain visual encodings globally, it requires designers to update each chart manually. These are common challenges for dashboards with many facets, which leads to further discussion in the next chapter. There are also minor

problems due to limitations in multiple view charts, where the auto-size feature cannot be applied successfully.

Overall, Vega-lite is quite effective for implementing the vast majority of data charts, although it lacks capabilities that go beyond the grammatical structure. As a result, the user session timeline requires more advanced tools to implement.

5.3 User session timeline in D3.js

The visualization design for the user session timeline does not fall into the standard dashboard library. The swim lanes of events require complicated architecture. D3.js is the most flexible in manipulating the DOM, which naturally becomes the suitable choice for implementing the third-page [41].

We adopted the same layered structure as the design to make the implementation process straightforward. As with prior pages, we began by creating a data sheet template to test the design. The imported session data set includes each row item as one event, with its start time, end time, and belonging categories specified. The data for prototyping are randomly generated to simulate actual user sessions. Then, we imported the data set and parsed it with D3 to begin the work. We regulate the global y-scale to match session id while the y-scale matches the maximum session length. Three sub-data arrays were created for the three layers of the timeline: background logged events and visualization views. We have also introduced color scales to group the events by their category. For visualization views, we imported texture.js to customize different textures in mono style to group the views. The color legends are also DOM elements that need to be implemented individually. In addition, we added the visible y-axis to provide a reference for session lengths and swim lanes between the sessions to clarify the reading order for users. As for interactivity, we need to make the choices due to limited time and available data. We decided to prioritize the interactive color legends for event categories, which is critical in identifying exploration patterns. When testing with real data, we stretched the view with a y-axis overflow, allowing more space for long sessions. D3.js also allows us to integrate animation APIs to sort out labels which prove to be critical in ensuring the usability in this page.

D3.js demonstrates its superiority over Vega-lite grammar in the construction of customizable visualizations and global scales, making the entire chart an elegant integration of SVG parts. However, there is no urgent need to create the simple charts using d3, for it requires much more time to learn and familiarize with the grammar.

Especially for non-experts building their first dashboards, starting the implementation in JavaScript does not lead to an easy way forward. While creating the dashboards, the multiple tools I used deepened our understanding of data visualization, which hopefully can gain insights into more generalized dashboard design.

Chapter 6

Evaluation and discoveries

The evaluation for Vistorian Dashboard focuses solely on testing the real data within the analysis team. The dashboard final design used real data to showcase the results. During the three-week evaluation process, we reflected on the preliminary dashboard prototypes, refined some blocks' design decisions to better suit the real data, and improved some detail loopholes that affect dashboard flexibility and usability. From the results, we discovered new insights about logging datasets and evaluate if the design answered research questions.

6.1 Evaluation methods

Evaluation stood as the final stage in the overall design process covering three weeks, while overlapped with the end of the implementation stage. To test the effectiveness and efficiency of Vistorian dashboard, we need to test from the perspective of our expert users and logged data. While the analysts are the end user of this dashboard, the designer also serves as part of the analyst team, which makes the designer its own user. The special role of the designer enables the evaluation to progress smoothly along with the implementation and facilitates the communication process for quick design iteration.

The evaluation process is a tight cooperation between Vistorian analysts and designers. It is not a one-time user testing experiment but a continuous discussion to improve the design. Analysts processed the raw data set of logged data and provided the calculation results grouped by their scientific methods of user categorization. Then the data were handed over to me as the dashboard designer to make secondary analysis visually in the dashboard. If the real data shows unclear results or fails to address the

intended task, we did quick iterations of other possible visual representations to improve our design decision on which one is the most effective. In the meantime, we evaluated the effectiveness in terms of testing data with the dashboard, summarized the usability issues, and made improvements to its interaction.

6.2 Evaluation results about usability

The results provided us with insights into usability assessment and task analysis insights. As the real data calculations took us quite a long time, we can improve the design and amend the loopholes multiple times in between the evaluation process.

Effective and reasonable visual encodings for dashboard components and interaction interface guarantees usability. For expert users, the usage scenario is mostly in a working desktop setting where it is easy to access large-screen interfaces. Thus, Vistorian Dashboard is easy to access on the browser and the larger screen provides clearer representation when the dashboard adjusts and resizes itself. The navigation is straightforward within one click. We analysts have built familiarity with each component's information as testing progressed.

Use interactivity to clarify visual overload

To balance a well-organized color encoding system with the turbulent real data, the compliment interactivity and animated transitions facilitate how analysts focus on statistical points. For instance, on the general page where Vistorian timeline (see Figure 4.3) is located in the middle, the interaction here can assist users to distinguish different shades of blue lines. In the user session timeline page, we added animated transitions to sort out densely distributed labels.

Create a neat workflow for future updates

For an analytics dashboard that requires frequent data updates, the data structure used in the dashboard and update workflow is a crucial part of dashboard design. During the process, the data went through initial cleaning from raw data, secondary analysis for the dashboard design, and then finally filled in the prepared data set the template for updates. A well-designed data set template can facilitate much repetitive work and maximize the productivity of dashboard performance.

6.3 Evaluation results about task analysis

When importing real data, we can evaluate whether the dashboard succeeds in answering high-level research questions and task analysis lists. We structured discussion sessions to share the insights about data with each other in Vistorian team. In this section, we propose the findings from visual analysis results through the dashboard.

Peak into Vistorian users in General page

As we glance through blocks on the first page, we get an overall sense of Vistorian user performances. The dashboard showcases user distribution from multiple angles (see Figure 6.1).

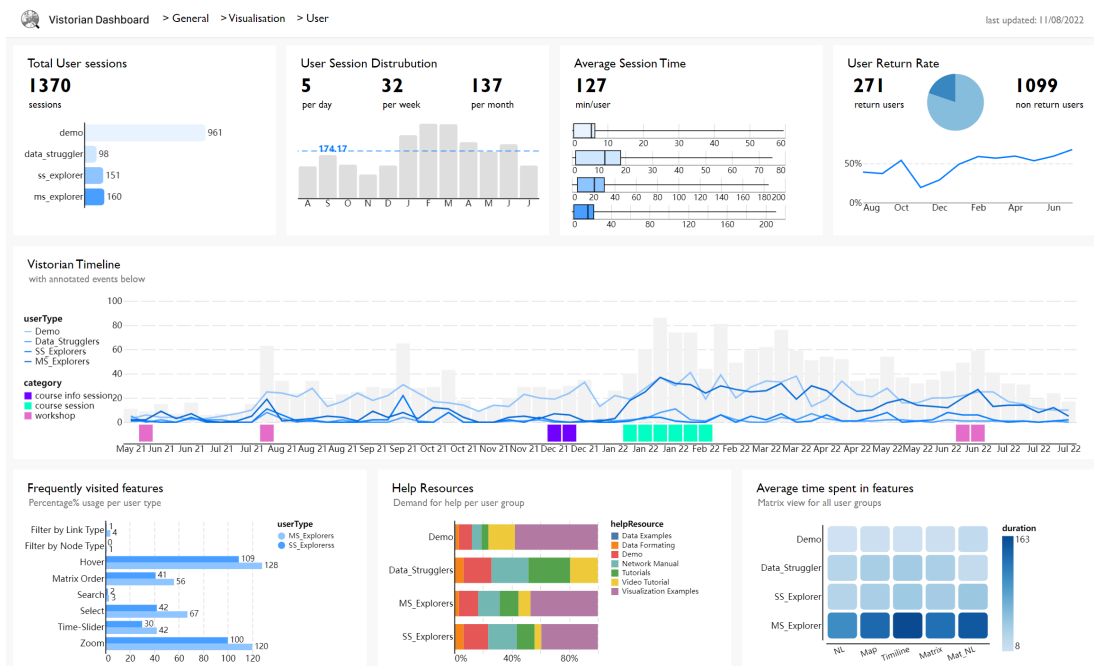


Figure 6.1: Evaluation of page general with real data

In terms of user types, demo users’ sessions took the majority part of all users. Together with data strugglers, we see almost 70% users did not reach the stage of successfully creating network visualizations. In terms of temporal changes in users, the Vistorian attract more users in the year 2022 than in 2021. Since the beginning of 2022, statistics including user sessions and return rates all have performed better than in 2021. The session duration for different users is distributed in the range of 10 to 30 minutes, while all four types of users have extreme cases extending over one or two hours.

The Vistorian timeline in the middle takes us into a more detailed view of what is happening across the yearly scope. It is especially very clear to see the user changes

closely correlated with the annotated events, for instance, there is a sharp increase in all four types of users when a workshop took place in mid-July 2021. Ever since the course about educating network visualizations started, there is an obvious increasing trend in users, especially in multiple session users who explored their own visualizations multiple times.

Next, we shift our eyes to what users are using in the third row. The overall feature preference is very intriguing that it led us to further question what features users prefer per visualization. The help resources function also reveals a logical explanation for categorizing the four different user types. Demo users who are the least expert in Vistorian spend more time in video tutorials than others. It also reveals potential problems like why barely anyone uses the data examples, especially for the data strugglers, which can guide analysts to further improve the learning process for those users. For the matrix block, we discarded two steps and focused on the exploration time spent in each visualization.

User activity in exploring different dynamic networks

As this page focus on visualizations, the targeted Vistorian users are single session and multiple session users. We can see their activity summaries in each diagram with the help of column view comparisons (see Figure 6.2).

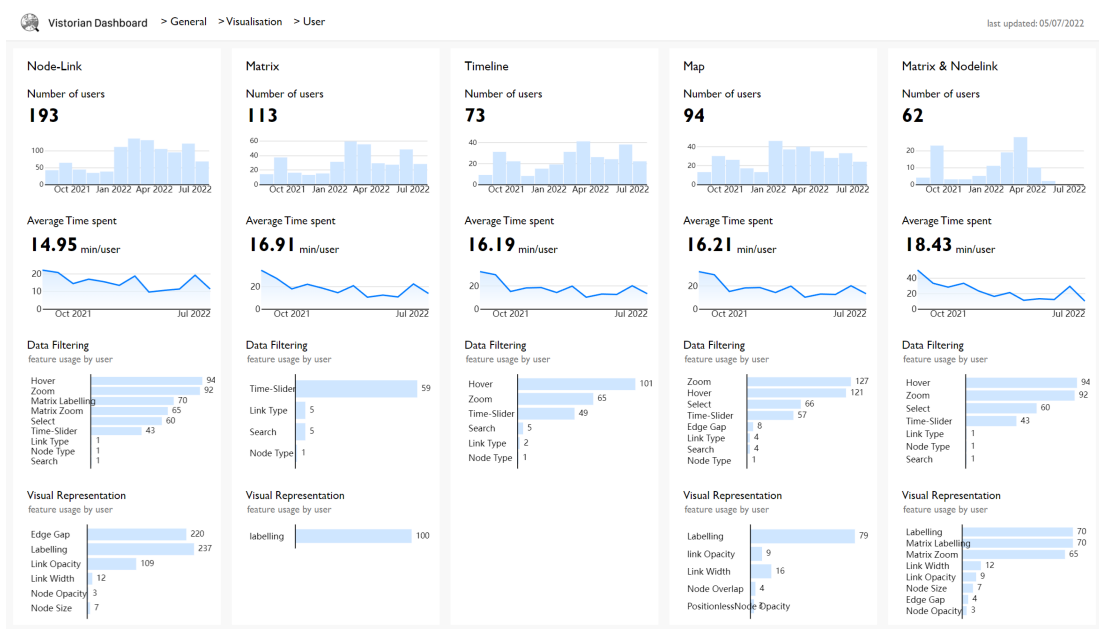


Figure 6.2: Evaluation of page visualization with real data

In terms of user distribution, it dissects the users according to visualization. The

node-link diagrams attract the most users, about double the user number compared with other views. The monthly distribution of users per visualization shows a similar trend as the total user distribution on the first page. For average session time, we can see there are also similar trends across visualizations, which indicates similar usage. Thus, we have second thoughts about improving this block by testing with other visualizations that can give us more insightful stories. One small problem is the Vega-lite temporal label configuration does not work very well in mini charts like these. The mouse hovering tooltips can help analysts clarify the exact date.

While the general page provided a frequently visited feature bar chart, feature usage on this page lists them all. When we make evaluations, we chose to use the direct number of users who used particular interactive features in the feature usage blocks. Because not all visualization diagrams have the same interaction techniques, the real data shows discrepancies, for example, timeline diagrams do not have unique interaction in visual formatting. We can see the most popular interactions matches the intuitive actions when faced with complex networks. For features affecting data filtering, users are interested in zoom, hover, and select, which allow users to focus on a particular data point. While Vistorian provides dynamic exploration through time, the time slider also attracts many users. The visual representation features are not always available in every diagram, but for those that provide them, the most popular ones allow users to see the cluster of relationships and nodes clearer. But interestingly, users prefer playing with link opacity a lot more than node opacity, showing their emphasis on nodes distribution.

User action individual characteristics and patterns in session timelines

While the two pages depict a summary from different angles, the session timeline serves as a microscope for individual users. With the interactive features provided by the dashboard, we can see how they use all the features just by glancing at the swim lanes (see Figure 6.3).

We sorted out the real data set from four users to finalize the design details. Different users drastically differ in their session time based on the user session blocks on the general page. We select users in the interval of the densest distribution of user session duration. When we run our testing, many unexpected problems occurred. The event durations are very short compared with the entire user session. Events frequently logged are very crowded and populated, making their labels overlap with each other. The densely displayed information caused great trouble for analysts to clearly see the user actions. To address these problems, we modified the final design in the following ways

(see Figure 6.3). Firstly, for the same events that occurred consecutively, we group them into one event with a longer duration, while for those events that happened in a single click, we mark them as one second to be visible in the timeline. Secondly, we removed some of the events which are not triggered by user actions to make the timeline more focused on user behaviors. Finally, we used animated transitions to allocate the labels by their sequence to avoid label clashes.

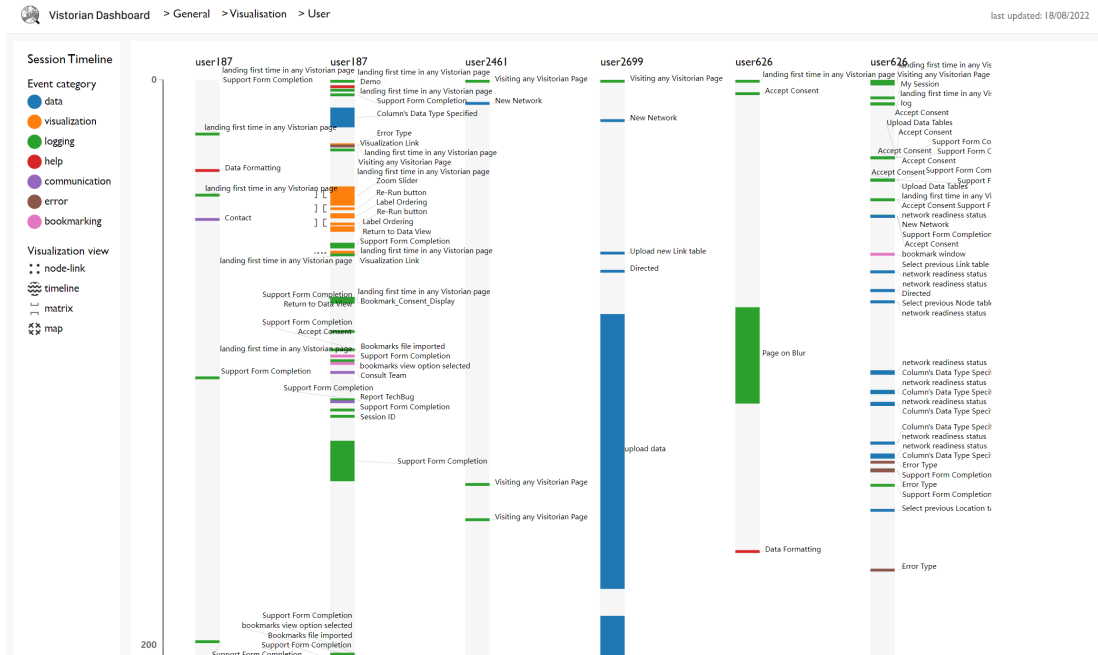


Figure 6.3: Evaluation of page user session timeline with real data

First of all, it can **verify the user categorization methods** by viewing their actual activities, whether or not did they enter the stage of visual exploration. Secondly, the timeline shows **cluster of interactions** in different phases, which contains usage patterns across different users. Demo users spent a lot of time browsing the tools, and very little time using the visualization examples. They are not sure which feature to use and click re-run many times. It has the potential to show different interaction cluster types between users as well. Combined with interaction in selecting the event categories, analysts can clearly see the distribution for each type of event. While exploring, they adopt a collection of preferred interactions like zoom to focus in certain nodes and links, which gives us more information regarding action sequence compared with the visualization page. Thirdly, the Y axis of the timeline measures the action length, where we can build **a sense of the temporal difference** for each user and compare them with others. For single-session users, the time spent formatting their data and

exploring visualizations varies. Some start their data uploads at the very beginning, and some spend more time back and forth amending their data. Finally, when focusing on **help resources**, the timeline can help us build speculations on whether they are helpful or not for facilitating the creation process. But in the sample data examined, we can see the two single session users who created networks never used the help once, while demo users used help multiple times. Furthermore, the session timeline indicates further research about how we should better categorize the events in Vistorian to better demonstrate usage patterns.

Chapter 7

Discussion

Reflecting on the entire process of Vistorian Dashboard design and evaluation results using real data, this chapter discusses what I've achieved and learned, including 1) how this analytical dashboard contributes to evaluating Vistorian network tools in terms of user patterns; 2) what I learned about dashboard design in the iterations. Finally, we expand this discussion towards future work about more generalized dashboard design.

7.1 Analytical dashboard supporting visualization evaluation

For user interaction logs collected in the wild, we have at hand a rich data set that can be used to evaluate user patterns in Vistorian tool. The dashboard proposed in this thesis provides a visual analytics solution that can organize and present data from different angles, from high-level overviews to focused user events.

The analytical dashboard succeeded in **reporting log data** comprehensively with depth. The three pages structure with blocks of visualizations answered the research question of how to visualize logs to present user performance and enhance analysts' understanding. In the dashboard, we report on different user types, session distribution, and feature usage in different perspectives of aggregate summaries, temporal change, diagram usage, and individual activity.

For analytical usage, Vistorian dashboard is created around tasks raised by the analytical team, using charts to provide insights into these tasks. During the creation process, it helped us in **identifying patterns** about user activity. When looking at multi-dimensional visual data at a glance, we can draw preliminary conclusions like

users' preference in using a different feature, and users' cluster actions in exploring the InfoVis tool.

Moreover, the evaluation process revealed new insights about the analytical dashboard that can be used to **verify calculations and assumptions** raised before we clean the data. The user type categorizations went through several stages. We can see from the dashboard if it shows robust consistency across charts to verify the user patterns assumption or find mismatches. At this point, we can use the dashboard results to raise new assumptions about the user dataset, which can lead to future research questions.

7.2 Reflection for effective dashboard design

The design journey of Vistorian dashboard leaves us valuable lessons about effective dashboard design, especially in our case of facing expert users. The final design relied on productive task analysis supporting content decisions, dashboard design patterns guiding a clear layout, and seamless cooperation allowing fast iteration. This section will discuss how we find an effective way to sort out design decisions.

While Vistorian dashboard serves expert users who already have high visual literacy, the obstacles in starting the first step of designing are comparatively low. We are our own users, thus the quick data visualization sketching in the beginning stage speed up the process to interpret data set features.

The task analysis sessions helped a lot in the early design stage. At that point, we do not have clean data that can be used and tested. The framework of "scenario, goals, and detailed tasks" serves to break high-level goals into actionable tasks. A structured task list cleared our thoughts in dashboard content decisions. Once we have the rough sketches, we can start organizing the data for specific usage.

As the tasks constitute the content, we need a set of explicit components to make the dashboard readable, semantically reasonable, and consistent in visual encodings. Here dashboard design patterns contribute as the go-to toolkits to assist the decision decisions. Finally, the evaluation takes up a critical step in the entire process. We rely greatly on the evaluation with real data to finalize all the blocks displayed on the dashboard. This step is directly related to the validity of the design results and cannot be ignored.

When implementing the dashboard on web pages, this thesis tried both high-level visualization grammar like Vega-lite for known standard charts and flexible d3.js to realize the session timeline. Both tools have their pros and cons, the tradeoff is between learnability for beginners and flexibility in the design customizations. The reason I

choose them is they both can meet the requirements of the designed visual encodings and data structure. However, neither tool is designed to suit the development of dashboards. The smoothness of the iteration process must be built on familiarity with developing tools and well-designed workflows in advance.

7.3 Limitations

While this thesis showcased the Vistorian dashboard design, there are many areas worth optimizing during the design process. Firstly, the final design sacrificed filtering interactions in most dashboard blocks to avoid hiding partial data. Yet there are still places filtering features can provide more insights than its shortcomings. For instance, the user session timeline would be able to contain more thorough information when filtered by session length or user type. Secondly, although the visualization page categorized features according to interaction taxonomies, there is still room for improvements in reporting the unique features in each diagram view. As for the dashboard usage workflow, there are limitations in the design of data files used, and implementation techniques. The current JSON files used to store data can be made into a standard template to facilitate updating and future changes. The blocks of visualizations which used repeated configurations can be further integrated into global variables. These specific detail improvements can lead to increase efficiency and refined workflow for future dashboard development.

7.4 Future work

The Vistorian Dashboard proposed in this thesis discussed using the dashboard as a tool to visually evaluate InfoVis logging data. There are not many cases in the visualization community that tried the dashboard or define their visual evaluation in the form of a dashboard. This research allows us to think about future research challenges in this exciting area. While this thesis embeds statistics for different user types within each page, how can we better interpret patterns from the perspective of different user types using the dashboards? When evaluating InfoVis user patterns, is there a way to design a generalized task list for researchers to tailor their analytical dashboards? Can we appropriate the methodology and design process in this thesis to other evaluations?

Based on the reflection on the iteration process, we feel the urge to research further in dashboard tools and improved workflows. While the dashboard proves to be effective

in identifying patterns and verifying data analysis assumptions, we put in laborious work in saving different result versions, constructing data files to enable updates, and configuring visual encodings in each component to achieve the ideals. This all directs future research questions in dashboard design. How can we provide assistance alongside the design process? What dashboard method framework can help designers avoid possible pitfalls and facilitate the process in advance? Is there a better dashboard development library that can optimize flexible design needs? All these future questions call on us to continue the work in the dashboard research community.

Chapter 8

Conclusion

This thesis presents Vistorian Dashboard to visualize interaction logs collected in the wild during 16 months period. The dashboard targets expert users among the analyst team. Using a task analysis with an iterative design process method, we identified the usage scenario as evaluating user visual analysis performance.

In the presented design, we assigned three main goals to three separate pages following a hierarchical structure. The general page depicts different types of users from different aspects including monthly distribution, session time, and key feature usage, giving a top-level overview of who is using the Vistorian, and how they perform. On the Visualization page, we compare the five views of dynamic networks' diagrams, showing user activity in terms of user distribution, session time, and preference in interaction techniques to conduct visual exploration. The user session timeline page visualizes individual sessions in swim lanes. Using colors to group user events categorically, the dashboard allows analysts to visually identify patterns in user action.

In implementing the dashboard, this thesis used both Vega-lite and d3.js and gave a summary description in comparing their pros and cons for dashboard development. It is critical to have a useful dashboard library that a smooth workflow can facilitate data updating, keep records of history versions, and maximize dashboard flexibility. The exercise of Vistorian Dashboard showcased the dashboard's adaptability in the visual analysis of evaluating InfoVis tools. From the evaluation results with real data, we succeeded in reporting logging data, identifying user activity patterns, answering our listed tasks, and verifying the analysis calculations. It uncovers valuable insights about users in the wild, from which we can raise new research questions for further analysis. The study does not end here but paves the way for future research about Vistorian users and more generalized research for effective dashboard design.

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