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Modeling the performance of interaction techniques for the comparison of spatial entities in the context of geo-dashboards

Bachelorthesis

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Submission date: November 15, 2023

Abstract

Contents

1 Introduction

The growing usage of dashboards to represent data across a range of different fields suggests a need for research on layout and design features of dashboards and their influence on the user experience. Previous research has shown that there is no one-fits-all solution for the design of dashboards [25, 20].

This existing agreement that general design recommendations for dashboards are not sufficient and/or possible ask for a breakdown of components that constitute dashboards. One approach is to identify user interactions that are possible when visualized data is explored or analysed. The field of geovisualizations and geodashboards is enriched with many different perspectives that all try to define taxonomies and or classifications models for possible user interactions [1, 7]. Many have their reasonable own application for spatial-temporal information visualization. But the minority of these classifications and taxonomies are empirically-derived. The proposed framework of Roth represents an exception. He has shown that a functional taxonomy of interaction primitives can be empirically derived. He identified general tasks users want to accomplish (objective primitives) [19]. Besides narrowing down the scope to one of Roths derived objective primitives this work will also look at this topic from the perspective of different interaction techniques.

An interaction technique as broadly defined in the Computer Science Handbook from 2004 is "the fusion of input and output, consisting of all hardware and software elements, that provides a way for the user to accomplish a task." [11]. Input describes all sensed information about the physical environment to the computer. Output from computers on the other hand include any emission or modification to the physical environment. In the context of geovisualizations and geodashboards, interaction techniques have been researched [12, 14, 21]. Roth also describes an interaction technique in the context of geovisualizations as the functionality of an given interface and the procedures of manipulating its visualizations [19].

This work will deal with the derived objective primitive of *comparison* from Roth's work. But not only Roth writes about comparison. Wehrend describes *compare* as a seperate operation class in visualization problem [24] and Brehmer et al. speak of comparison as a low level visualization task [3]. Also Buja et al. propose *comparison* to be one of the three fundamental plot manipulations in data visualization [4]. In the scope of geovisualizations Crampton identified *compare* as an interactivity task [7] and Gorte and Degbelo argue that *comparison* is a basic task that is relevant in exploratoy and confirmatory analysis [10]. Buja distingiushes between two dimensions of comparison. The first describes the goal of comparing different variables or projections of the whoel dataset. The second describes the goal of comparing subsets of the whole dataset against each other [4]. This work will only focus on the latter.

We will examine two broadly used interaction techniques: *filtering* and *highlighting* [12, 19]. Keim et al. describe *filtering* as a combination of selection and view enhancement and Roth attributes filtering to identifying matches from user-defined conditions. The literature often use the term *brushing* to describe *highlighting*. They can be considered synonymous in the scope of interaction techniques as both describe the process of visualy emphasizing a subset from the whole dataset. Historically to define the subset the process started by drawing a rectangle directly in the view with the mouse which was called *brush*. Which explains the term *brushing*. For the rest of this work we will use the term *highlighting*. Keim et al. state that *highlighting* is often combined with linking which describes the process of selected data beeing communicated to other views of the data. They follow one of the proposed user strategies *Select Subset* from Gleicher [9].

In this work we will investigate how these interaction techniques influence user performance in the context of comparing subsets in geodashboards. Because the interaction technique is by far not the only variable that can be changed, we also want to observe the influence of different variables on the user performance. To provide a starting point backed with emperical data we want to derive a mathematical model that should display user performance in dependence from different variables which are described later. Therefore we can infer two research questions for this work:

1. Which mathematical models best describe user performance during the comparison of spatial entities in the context of geodashboards?

2. Which interaction technique best supports the task of comparison in the context of geodashboards?

To answer these questions we conducted a user study in which participants try to answer questions with the goal of finding differences and/or similarities of subsets of spatial-/temporal datasets. To answer the questions they are using a specially builded digital web-prototype with six different dashboard variants. The dashboards vary in their interaction technique and some render additional views utilizing *explicit encoding* as it is defined as one of the basic designs for visual comparison [9]. The goal of the experiment is to collect data about the user performance. We have defined user performance to be two dimensional. First want to know about the time it takes to answer questions. It is important to note that it does not matter wether a correct answer was given. The second dimension is about accuracy. This seperatly tracks wether an answer was correct or not. After collecting the data we want to use that data to derive mathematical models that best approximate answer time and accuracy during the comparison of features in geodashboards. With special interest for the differences between the selected interaction techniques. We want to learn about the different factors we have included and how they influence answer time and accuracy in this setting.

To get an overview of the current state of research, chapter 2 will provide information about scientific contributions on interaction techniques in geo-dashboards and comparison. We will also give an short introduction to multiple coordinated because we are utilizing such a system in our prototype. Section 3 will describe key concepts of the mathematical models and what constitues them. In Section 4 details about the digital web-prototype and how it was built are presented. How the experiment was designed and what factors that possibly influence comparison performance were considered are covered in section 5. Section 6 will present the results of the experiment and propose our found mathematical models that showed the best testing results. As this experiment only covers a selection of possible factors that possible influence difficulty and accuracy during the comparison of features in geodashboards, this work should be a starting point for further research. Because comparison can be of many different kinds and cover different scopes this work also opens the door for more reseach in different comparison settings. Section 7 discusses such limitations in depth, how our research questions can be answered and how our findings can be transferred to other domains. Lastly we will sumarize our key-learnings and propose future work that has to be done in section 8.

2 Related Work

In this chapter we want to summarize existing research with regard to our two interaction techniques: *highlighting* and *filtering*. First we will look at how the use of *highlighting* and *filtering* in the context of geodashboards is analysed. Second, we will also examine the interaction techniques in the context of multiple coordinated views because of its central role in our web-prototype.

2.1 Interaction technqiues & Geo-dashboards

see legends of the dashboard

2.2 Interaction techniques & Multiple coordinated views

Multiple Coordinated Views (in the following abbreviated with 'MCV') is a specific exploratory visualization technique that allow users to explore data. It consists of multiple views that all encode the same data in different representations. Interactions and operations of the user are managed and synchronised between views [18]. Buja et al. argue that beeing able to pose queries graphically and viewing the response in the same visual field is a fundamental component [4]. The principle is extensivly accepted and researched and proven to increase user performance, discovery of unforeseen relationships and unification of the desktop [16]. Buja et al. even include it in their taxonomy for data visualization. They even mention *highlighting*, one of our two researched interaction techniques, to often be a substantial part of MCV as it is one way pose queries about subsets graphically [4].

Because of its popularity 20-30 years ago much of previous research in the field of MCV focused on scatterplot matrices [5, 2]. Lawrence et al. used a specfic tool for the exploratory analysis of systems biology data and showed how *highlighting* is an effective technique for discovering outliers [13]. Carr et al. argue that *highlighting* is the most common interaction technique in scatterplot matrices when working with subsets [5, 2]. On the other hand they argue that if the subsets becomes larger another approach may be more suitable. They called it *specify, then compute.* The idea is that a selection region is defined, similar to the highlighting procedure, then the subset is computed and finally a new display is rendered that only contains the subset. This describes our more modern idea of *filtering.*

Some contributions on interaction techniques in MCV systems define *filtering* as a type of *highlighting* (*brushing*) [23].

2.3 Comparison

Gleicher writes about four considerations when visualizing comparison [9]. At first we have to identify our comparison elements. Because every comparison task in our study focuses on comparing two or three features of the dataset we can descibe our targets as 'explicit targets' as every item is known and already available. From Gleichers proposed actions on relationships between targets our comparison task fall into the *Identify* and *Measure/Quantify/Summarize* categories. Second we have to identify comparitive challenges. The number of targets should not add much complexity as we are only using two or three targets. Because we are using timeseries with only one observed variable the complexity of each individual item is also fairly low. As we are only identifying and measuring direct differences or differences between differences of targets the complexity of the relationships is low to moderate. Gleicher next proposes to deal with a scalability strategie. To reduce scale challenges the strategies of *Select Subset* and *Summarize Somehow* are utilized. In all dashboard variants either *filtering* or *highlighting* as an interaction technique is used which help with scale because subsets are created. In some variants additional views are rendered that already encode the difference of two targets which summarize a relation. Lastly we have to consider design visualizations. Across all dashboard variants all three basic visual designs for comparison are utilized as each have their benefits and drawbacks. Because we deal with temporal data all graph views are utilizing *superposition.* To reduce scalability problems either *filtering* or *highlighting* are utilized as already mentioned. Our table views use a combination of *super* - and *juxtapostion* as showing each datapoint in the same place would hinder readability. Finally because our actions on the targets include comparing differences between targets we included *explicit encoding* in some dashboard variants.

3 Digital Web-prototype

The prototype is created with the open source web development framework next.js, which offers react-based javascript- or typescript-based applications with server-side rendering and static website generation. It is mostly selected because of its developer-friendly ecosystem especially regarding deployement. Another reason for this stack is the existing experience with react-based typescript and the light-weight, modern setup. The whole application is using of a few react libraries. The most important beeing the popular "react-leaflet" library which drastically simplifies the use of leaflet maps in react applications. Other important libraries are: "zustand" to help with coordination, "recharts" to help building time lines and "tailwindcss" to simplify the design process of the application. Because the experiment is designed to be held online the application needs to be deployed. For that we use the free deployment plan of vercel.com. Because the application is only using non-personal static data there is no need for implementing a backend or an authentication system. Although the prototype takes responsive behaviour into account the screen dimension of the user's device should not fall below 1280x720px.

3.1 Data

The data used in the web-prototype consists of two components. First we implement geodata of the states of germany. In terms of performance, low-resolution geojson data with a reference scale of 1:5000000 is used. We utilize the open-source data from the german federal agency for cartography and geodesy [8]. The questions in the study are about static spatio-temporal datasets focusing on changes of thematic properties expressed through values of attributes. Meaning qualitative changes with numeric characteristics. According to Andrienko et al. this is one of three types of spatio-temporal data [1]. On the other hand spatio-temporal datasets can have existential changes, features appear and disappear over time, or they can have changes in their spatial properties. Because we want to minimize learning effects when using the data and because every participant is going to answer eight questions, we implement four different datasets. The dataset is switched after every question using the "dataset control" which will be explained later. All four datasets have the exact same structure. They are about qualitative numeric changes of one marker of all 16 states of germany and covered the years from 2008 to 2022.

3.2 Interaction techniques

In addition to the methods already presented: *filtering* and *highlighting*, we decide to investigate a third method. It is a modification of the highlighting method. When features are selected for comparison, they are visually highlighted using *different* colors. In classic highlighting, all selected features are highlighted in the *same* color. For the rest of this work we will distinguish highlighting using the same color and highlighting using different colors by naming the first *highlighting_1* and the second *highlighting_2*.

3.3 Layout & Function

In addition to the static data, the entire application consists of a simple frontend that serves six different non-scrollable geodashboard variants. Always two of the six variants implement the same interaction technique. Variant 1 & 4 use *filtering*, variant 2 & 5 use *highlighting_1* and variant 3 & 6 use *highlighting_2* (see Table 3.1). When accessing the prototype the first variant is rendered. The other variants are reachable over a tab-based navigationbar at the top of the screen. A seventh tab is implemented to learn about the application and its purpose. Each variant is covered with an openstreet map that is centered on Germany stretching over the whole page. All states of Germany are rendered using the borders as polygon representations. Every polygon used the same blue fill color. All other elements in the dashboards are placed on top of this map. On every variant, two additional views are also rendered on top of each other, taking up the left third of the screen. The time chart in the top-left corner of the screen visualizes the spatial temporal data by rendering 16 lines, each representing one of the 16 states of germany. The bottom-left view visualizes a two-dimensional table connecting each state with each year containing a numerical value. The "dataset control" and another button, which will be termed "comparison control" are positioned in the middle third of the screen close to the navigationbar at the top. The comparison control offers the ability to select two or three of the 16 states for comparison. After selecting the states and confirming the comparison process the application enters "comparison mode" where three of the six variants render an additional time chart and an additional table view. In both views calculated differences between two states of the values of the selected states are displayed. In the time chart again consists of lines representing the temporal evolution of the differences and the table view contains the numerical differences as simple numerical values for every year. Those are the already mentioned views that use *explicit encoding* as defined by Gleicher [9]. After starting the comparison process both views on the left are replaced with other views depending on the interaction technique. *Replace* is one of the three common operational models visual interfaces use on parameter change [6, 17]. At any time the user can use the comparison control again to terminate the comparison process and all previously described changes are reverted. The "dataset control" on the other hand allows the user to change the currently selected dataset via button click. After switching the dataset all views are rerendered with new labels and values.

Variant	**Interaction technique**	**Number of views**
1	filtering	2
2	highlighting_1	2
3	highlighting_2	2
4	filtering	4
5	highlighting_1	4
6	highlighting_2	4

Table 3.1: This table describes all dashboard variants visualized in the web-prototype. The number of views it rendered in "comparison mode" and the interaction technique is displayed

3.4 Multiple coordinated views

As already stated earlier MCV systems are highly popular and can increase user performance. Baldonado et al. argue that they can provide utility by minimizing cognitive overhead created from a single complex view. On the other hand multiple view can also increase cognitive overhead (e.g. context switching) and can raise system requirements. They propose guidelines to find out when to use MCV and how to use MCV with special focus on information visualization [22]. One use of MCV in the prototype is the additional rendering of two views when entering the "comparison mode". This mechanism represents the stated example from Baldonado et al. of using MCV to display aggregates of the data. The rule of "Decomposition" motivated the use of additional views that aggregate differences when user are asked about differences in the first place. As the name MCV already suggest "coordination" is a really important factor when implementing multiple views. Baldonado et al. devoted two guideline rules on this because multiple views if not coordinated corectly can create confusion and increase computational overhead. Because of that all our interaction techniques are synchronized across all views. Meaning if one element is highlighted in one view, it is highlighted in all views. When entering the "comparison mode" the specific interaction technique is also applied to all views. We also try to optimize screen space by replacing views when entering "comparison mode" or optionally render the additional views that aggregate the differences. In that way the "comparison mode" ensures that the additional data is only displayed when the user is aking for it. We ensure that the use of more views does not noticeable increase response time when interaction with the application. Finally we use perceptual cues to indicate replacement of views by animating the time line drawing on inital render and by changing the labels of the views when changing that datasets. To further support the "Rule of consistency" we synchronize the "comparison control" and the "dataset control" across all six variants, to reduce the computational overhead from context switching.

3.5 Non-/Functionl requirements

This section describes all functional and non-functional requirements on the web-prototype. They are the result from the topics explained earlier in this chapter.

Nr.	**Requirement**	**Type**
01	The app should visualize one spatial-temporal dataset with polygons on a map. Each polygon should represent a spatial entity	Functional
02	The app should allow the user to read the exact attribute value for every spatial entity over the whole time period in a separate view	Functional
03	The app should visualize the temporal evolution for the attribute values of all spatial entities at a glance in a separate view	Functional
04	The app eases the process of comparing two (or three) spatial entities through a comparison mode that can be switched on/off	Functional

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Nr.	**Requirement**	**Type**
05	The app should provide six different dashboard versions that differ in their interaction technique and number of rendered views for comparing spatial entities	Functional
06	The app consists of version 1 where in comparison mode only the selected entities are filtered and shown in all views. It represents a 'filtering' interaction technique	Functional
07	The app consists of version 2 where in comparison mode the selected entities are visually emphasized using one color. It represents a 'highlighting' interaction technique	Functional
08	The app consists of version 3 where in comparison mode the selected entities are visually emphasized using multiple colors. One for each entity. It represents a 'highlighting' interaction technique	Functional
09	The app consists of version 4 which is a copy of version 1 described in requirement 06. In addition, one more view that meets requirement 02 and one more view that meets requirement 03 are displayed in comparison mode. These additional views encode the subtracted values of the selected entities forming views that encode 'differences'. For every combination of the selected entities one additional data series is displayed.	Functional
10	The app consists of version 5 which is a copy of version 2 described in requirement 07. In addition, one more view that meets requirement 02 and one more view that meets requirement 03 are displayed in comparison mode. These additional views encode the subtracted values of the selected entities forming views that encode 'differences'. For every combination of the selected entities one additional data series is displayed.	Functional

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Nr.	Requirement	Type
11	The app consists of version 6 which is a copy of version 3 described in requirement 06. In addition, one more view that meets requirement 02 and one more view that meets requirement 03 are displayed in comparison mode. These additional views encode the subtracted values of the selected entities forming views that encode 'differences'. For every combination of the selected entities one additional data series is displayed. In line with version 6, which represents a highlighting interaction technique with individual colors, the rendered differences are also visually highlighted in different colors.	Functional
12	In all six versions in comparison mode all selected spatial entities are highlighted on the map.	Functional
13	The app enables the user to switch between four selected datasets which all have the same spatial-temporal dimensions	Functional
14	The app should be available over a website	Non-Functional
15	The app should be user-friendly and have fast loading times	Non-Functional
16	The app should use multi-coordinated views appropriately by paying attention to common guidelines to reduce cognitive overhead.	Non-Functional

Table 3.2: This table describes all functional and non-functional requirements of the web-prototype

4 User Study

4.1 Goal

The goal of the study was to find mathematical models that approximate user performance best. In our definition user performance is two-folded: time the user needed to give an answer (in the following abbreviated with *answer time*) and accuracy of that answer. The accuracy (in the following abbreviated with *answer accuracy*) is measured binary, meaning an answer could be true or false. We hope to learn something about the impact interaction techniques have on these two parameters. The findings refer to the scope of comparing features in geo-dashboards. Ideally we find differences between our three interaction techniques *filtering*, *highlighting_1* and *highlighting_2*.

4.2 Variables

We wanted to include several independent variables to get a rough idea of which factors would affect user performance when the goal is comparison of features in geo-dashboards. We also included multiple independent variables because we wanted to make sure that we gather enough observations and because of a reason explained in chapter 5. We included the number of views the dashboard renders, the number of spatial entities that are compared simultaneously, the interaction technique the dashboard used and the type of comparison question that was asked. We will abbreviate the number of spatial entities that are compared as *number of comparison targets* and the type of comparison question as *question type*. As already explained half of the dashboard variants had the ability to render two additional views that encode differences of the selected spatial entities. The number of comparison targets a comparitive question could be asked about was two or three. Gleicher states that the number of comparison targets directly influences the difficulty of the comparison [9]. The question type describes the kind of comparitive question that was asked. We used a total of four different question types, which will be explained later in chapter 5. As indicated already our dependent variables are answer time and answer accuracy.

4.3 Participants

The study involved twelve participants. All were between 20 and 29 years old. It included eleven male and one female participant. Nine participant stated to have no experience in the usage of geo-dashboard. Two reported to use geo-dashboards at least once a year. And one particpant stated to use geo-dashboards at least once every three months. Because the study was conducted in german all participants had to able to speak and understand german.

4.4 Design

The study followed a within-group design as each participant answered questions with all instances of every independent variable. With exception of the interaction technique where every particpant was exposed to only two of the three possiblities. Every participant had to answer half of the questions about two and the other half about three spatial entities. Every participant also had to answer half of the questions using 2 and the other half using 4 views. As the influence of the interaction technique was of highest interest, followed by the number of views and number of statial entities counterbalancing these factors was of highest priority. By limiting the count of participants to twelve we balanced all possible combinations of two interaction techniques across all study sessions (taking order into account). Every possible combination was used two times. To balance number of spatial entities, half of the participants answered the questions about two entities first and half of the participants answered the ones about three entities first. The number of views was treated similar but it was taken care of this balancing to be also balanced across all study sessions. Only the question type was not completly balanced as it would have requirement far more participants. Because the question type was more of a tool to observe the effect of the other variables this is not detrimental to the results. Every participant answered the same eight questions using all for questions types but using different orders. To reduce learning effects from the data we controlled the knowledge about it by changing the dataset after every question. Because of the dataset exchange we needed to control the datasets. All had the same structure and recorded qualitative changes of one numerical variable in the 16 states of germany between the years 2008 and 2022.

4.5 Procedure & Apparatus

The study was designed to be held online. The participant and the study coordinator met inside an online video conference. Before the session, the participant had to sign the consent form. The experiment required between 20 and 30 minutes of time. Before the experiment began, the study coordinator provided two links and a video recording. The video recording was a standardized of informing the participant about whats going to follow and included information about the prototype and how to use it. The first link led to the web-prototype and the second provided the online questionnaire used to propose the questions and track the answers and the answer times. If the participant had no further questions the particpant was asked to start with the first questions in the questionnaire. The first questions asked about some general information. After that the main part of the experiment began where the participant had to answer eight questions in succession. The questions are visible in the appendix. It was not communicated that answering quickly and right was of relevance. After each question the dashboard variant and the dataset had to be switched. This information was described and visually highlighted at the beginning of each question in the online questionnaire. After the main part of the experiment the particpant had to answer three more questions about subjective feedback regarding the two dashboard variants he/she used:

1. What and why did you like and dislike about the first dashboard variant?
2. What and why did you like and dislike about the second dashboard variant?
3. If you had to choose, which of the two dashboard variants would you prefer? Why would you prefer it?

After that the experiment session was closed by given the particpant the opportunity to ask questions. Before the start of the experiment the participant was asked to close any disturbing software and share their screen. The particpant also had to make sure to be in an undisturbing environment. The particpant had to use a terminal device with a screen size of at least 1280x720px. If one of these requirements was not met or the particpant was interrupted during the experiment the session was terminated and the results were not considered in the analysis.

The online questionnaire tool 'limeSurvey' was used to ask the questions and track the answers and answer times. After every experiment session the study coordinator had to rearange the questions and edit the hints about the dashboard variant and dataset to use. To have a chance of restoring answer times, answer accuracy and subjective feedback in case of losses each experiment session was audio and video recorded.

5 Mathematical models

Because our dataset is limited, we use linear regression to try to derive a function that explains how a possible connection between user performance and our independent variables looks. We decided against machine learning because it requires much more data to be effective. Because of our decision to use linear regression we had another reason to include several independent variables to gather enough observations because at least 10 different observations per independent varaible are needed to build regression models that deliver good results (quelle).

5.1 Aggregated Variables

Because our study used two nominal scaled variables and we want to analyse the results using linear regression we follow the process of builded aggregated variables. Those aggregated variables encode the different instances of the nominal scaled variables into continuous variables, which in turn enables linear regression. This requires existing knowledge, preferably empirically proven.

5.2 Answer time

First we want to look at the user performance in terms of their answer time. Because we have so little data available and because it simplifies the analysis process, we decided to include all data points, even if the answer was incorrect. Inspired by Fitts' Law, which is often used in HCI (human computer interaction) we focus on one possible aspect of answer time. An index that describes the level of difficulty of the task to which the user has given an answer.

$$Answer_{time} = a_0 + a_1 * Index_{difficulty} + a_2 * X_2 + \cdots + a_n * X_n \tag{5.1}$$

$Index_{difficulty}$	: difficulty of a specific question using one specific dashboard variant
a_0	: intercept
a_1	: coefficient of the difficulty index
$X_2 \dots X_n$	: other factors that also influence the answer time
$a_2 \dots a_n$	: coefficients of other factors

We now want to look how all our independent variables influenced the difficulty index.

5.2.1 Number of views

One of the rationales of MCV is that more views on the same data, help with data exploration. As we have already seen, if MCV is applied correctly, cognitive overhead is reduced compared to the same application not using multiple views. Because comparison is a type of data exploration we can assume that more views also help increase user performance in tasks that involve comparison. We can assume:

1. A higher number of views on the same data will reduce the difficulty index.

5.2.2 Quality of views

The suitability of views change across different contexts. One context for example is what task is tried to be solved using the view. In our experiment, we used a total of four different task types, which are represented by the four question types. Half of the questions ask for comparison of numerical(*attribute in space*) information and the other half asks for comparison of temporal(*space in time*) information. Those two question types are also listed in Roth's taxonomy of interaction primitives as operand primitives [19]. Lohse et al. classify visual representations(views) depending on the type of information conveyed. They classified 11 different view types and empircally derived likert scores(1-9) for every type of information [15]. Among other things they classified *time charts* and *tables* when dealing with *temporal* or *numerical* information. As the *attribute in space* operand asks for *numerical* information and the *space in time* operand asks for *temporal* information, we can use these empircal likert scores to quantify the quality of the table and time chart used when answering a specific question. Since each interaction technique renders at least one table and one time chart and we cannot predict which view the user will use, we need to calculate the mean view quality of both views for a given question type. The likert scale ranges from 1 to 9, meaning if a visualization is rated 9, it conveys the information one hundred percent. In our calculation we devide the likert scores by 9 to account for this. The following equation uses the likert scores from the tables and the time charts visualizations:

$$q_{view} = \begin{cases} \frac{8.0/9+4.5/9}{2} \approx 0.69, & \text{if } question\_type == attribute\_in\_space \\ \frac{1.8/9+7.8/9}{2} \approx 0.53, & \text{if } question\_type == space\_in\_time \end{cases} \tag{5.2}$$

In the experiment the question types have a second dimension. Questions could also either be of type *identify* or *measure*. In our mathematical model we do not distinguish between these two types because we lack research that would help quantify view quality in those regards. We can conclude with the following assumption:

2. A higher encoding quality of the views regarding the type of question will reduce the difficulty index

5.2.3 Distraction index

Finally we look at the concept of distraction. Through personal observation we concluded that the key difference of our three interaction techniques can be found in the prevailing distraction. In all our questions we want to find specifc values of our spatio-temporal data. Therefore all other possible values on the dashboard interface can act as *distractors*. Distractors have ranging distraction impact depending on their *similarity* to the searched value. When a user starts the comparison process the effect of the different interaction techniques take place. We can count the number of distractors displayed that could theoretically be confused with the value that is looked for. We can multiple the distractors with a weigth that represents the impact of each individual distractor. Because all interaction techniques follow the principle of visually emphasizing the selected target states from the remaining states we have decided to distinguish between two cases. From now on we classify each distractor as either *similar distractor* containing all distractors that look really similar to the target value or as *background distractor* containing all distractors that look really different from the target value but still exist on the dashboard interface and could also be mistaken to be the target value. As we lack research for quantifing the weights of the different distractors, we decided that the similar distractors are twice as distracting as the background distractors. To compute the overall distraction all similar distractors and background distractors are counted and multiplied with their respective weight resulting in a value that has to be divided by two because a user will only use one of the two views (table view & time chart view) simultaneously and both views encode the same information. This is the same principle described earlier for the view quality. The resulting value is called the *distraction index*. The number of comparison targets also impact the distraction because now more values are similar distractors, resulting in a higher distraction index. This also supports our earlier presented finding of a higher number of comparison targets increasing the difficulty of the comparison process. The distraction index is further influenced from the question type, our third independent variable. Because *measure* and *space in time* both ask for multiple target values that are required to answer the question, the user has to search multiple times. In this case everything is counted the same only with reduced *similar distractors*. We also account for the multiple searches the user has to perform by adding the not yet found target values in every search to the distraction index, getting less with every completed search. Finally, the number of views in connection with the question type also has an influence on the distraction index. Summarizing we can say that the additional views on the right side on the dashboard variants with the four views add similar distractors and background distractors depending on the question type. Questions with the question type *measure* ask for differences between comparison targets and therefore the additional views on the right side also contain target values along with some *similar distractors*. On the other hand questions that are of type *identify* never ask for differences between comparison targets, which is why the additional views only add background distractors. We can compute the distraction each view generates using this formula:

$$View_{distraction} = \alpha * (N_{distractor\_similar} * \beta + N_{distracor\_background} * \gamma) \tag{5.3}$$

$N_{distractor\_similar}$	: number of similar distractors
$N_{distractor\_background}$	: number of background distractors
α	: coefficient of the distraction of a view
β	: multiplier for the similar distractors
γ	: multiplier for the background distractors

In the analysis we will set $\beta = 1$ and therefore $\gamma = 0.5$. The coefficient α will be manipulated in the analysis later. We calculate the distraction each of the four possible views generates. We abbreviate the four views by their absolute position on the dashboard (UL = upper left, LL = lower left, UR = upper right, LR = lower right). Like on the view quality, we need to calculate the mean of the distraction scores of the table view and the time chart view, because one user will search and find the information in only one of the two views.The final formula for calculating the distraction index looks like this:

$$Index_{distraction} = \frac{UL_{distraction} + LL_{distraction} + UR_{distraction} + LR_{distraction}}{2} \tag{5.4}$$

Because the distraction index encapsulates the toal distraction the user experiences when answering a comparitive question on one of the dashboard variants, we can derive:

3. A higher distraction index will increase the difficulty index.

5.2.4 Difficulty index

The aggregation of all of our variables lead to following formula discribing the difficulty index:

$$Index_{difficulty} = b_0 + \frac{b_1}{n_{view}} + \frac{b_2}{q_{view}} + b_3 * Index_{distraction} \tag{5.5}$$

5.3 Answer accuracy

As already explained the answer accuracy was measured binary and therefore multiple linear regression is not an option. Instead we will use the method of logistic regression to analyse the results. When thinking of factors that could influence the accuracy of an answer we made the following assumptions. Because answer time does not matter for the accuracy we concluded that no factor can impede the accuracy of the answer besides the distraction that is present on the dashboard. A user can mistakenly confuse the correct answer with all distractors present. We call this variable the discriminability. As with the answer time there are more unknown and unobserved variables that have an varying impact on the answer accuracy. We conclude:

$$Answer_{accuracy} = a_0 + a_1 * Index_{discriminability} + a_2 * X_2 + \cdots + a_n * X_n \tag{5.6}$$

$Index_{discriminability}$: discriminability of the target value
a_0 : intercept
a_1 : coefficient of the discriminability index
$X_2 \dots X_n$: other factors that also influence the answer accuracy
$a_2 \dots a_n$: coefficients of other factors

5.3.1 Discriminability index

The discriminability is basically the multiplicative inverse of the distraction index. When no distractor is present the user will always answer every question correctly.

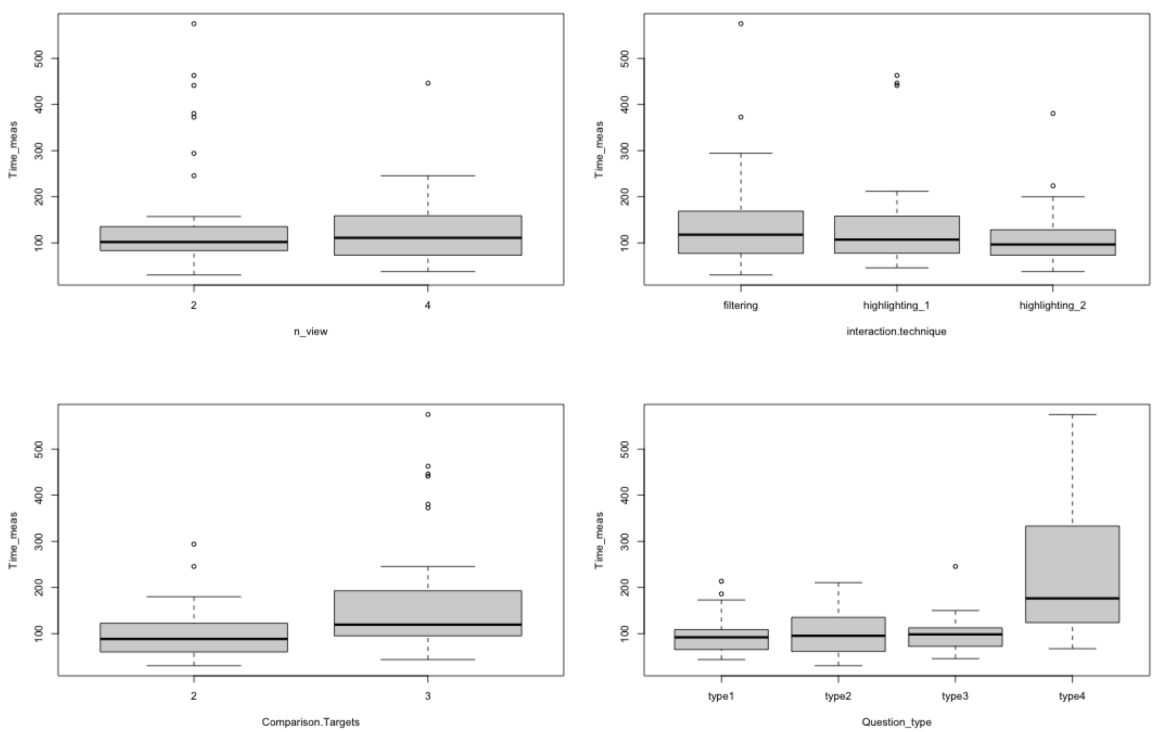
With a rising number of distractors the chance of mixing up the target values is increasing. Like before we have to account for different distraction qualities. Different distractors have different distraction qualities because of their visual appearance. It is the exact same observation that is covered with the distraction index. Because of this we will reuse it in the formular for the discriminability index:

$$Index_{discriminability} = \frac{1}{1 + Index_{distraction}} \tag{5.7}$$

6 Evaluation

As our study pursued an exploratory approach the evaluation was an experimental task. We had to think about variables that are sensible to manipulate and could impact the results.

6.1 Answer time



6.1.1 Manipulating the distraction index

Weil gesehen dass distraction index nicht gut korelliert, wir haben folgendes versucht

We decided to manipulate the distraction index in two ways and look how it impacts the results.

1. Manipulating α of 5.3

2. Manipulating b_3 of 5.5 (Distraction index as a whole)

6.2 Answer accuracy

6.2.1 Manipulating the discriminability index

7 Discussion

8 Conclusion

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