Exploring Information Visualization – Describing Different Interaction Patterns

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ABSTRACT

Interactive Information Visualization methods engage users in exploratory behavior. Detailed information about such processes can help developers to improve the design of such methods. The following study which is based on software logging describes patterns of such behavior in more detail. Subjects in our study engaged in some activities (e.g. adding data, changing form of visualization) significantly more than in others. They adapted their activity patterns to different tasks, but not fundamentally so. In addition, subjects adopted very systematic sequences of actions. These sequences were quite similar across the whole sample, thus indicating that such sequences might reflect specific problem solving behavior. Davidson's [7] framework of problem solving behavior is used to interpret the results. More research is necessary to show whether similar interaction patterns can be found for the usage of other InfoVis methodologies as well.

Categories and Subject Descriptors

H.5.2 [Information Interfaces and Presentation]: User Interfaces - *evaluation/methodology*

General Terms

Design

Keywords

Evaluation, exploratory Information Visualization, insight, problem solving, perception, interaction, software logging.

1. INTRODUCTION

The usage of Information Visualization methods (InfoVis) is often described as an exploratory process yielding complex insights [2]. In the following text, we want to describe a study investigating the exploratory activities of the users of an InfoVis method. We are especially interested in how users interact with an InfoVis method and whether common activity patterns can be observed among users. To do this, we use software logging to clarify the dynamic character of this process. We assume that information about how people use InfoVis methodologies might help to design tools more adapted to human needs and, more generally, to get insights about the reasoning processes adopted by users of information visualizations.

The InfoVis method the subjects used is called Gravi++ and was developed during a project called in2vis. The goal of this project is to support therapists in their work with anorectic young women. These women, and also their parents, have to fill in numerous questionnaires before, during and after the therapy. Interesting variables in this context might be, e.g., depression or number of friends the patients have. The therapists need these data to clarify which factors influence the success or failure of the therapy, that is, they want to find predictors. We tested the usability as well as the utility of Gravi++ quite extensively (see [29, 30]). The following study rather aims at finding out what strategies persons use when solving problems with InfoVis methodologies.

2. RELATED WORK: EVALUATION AND COGNITIVE SCIENCE

Amar and Stasko point out that the tasks users of current InfoVis methods might want to accomplish are on a higher level and differ significantly from tasks which can be supported by databases or many earlier InfoVis methods [1]. To describe the results of such a task, the term insight is sometimes used (see e.g., [32, 33]). This reflects that InfoVis methods increasingly represent information from ill-structured domains. In such domains, there are usually no straightforward methods of finding solutions, and searching for information is an iterative process of hypothesis-generation and verification. Apart from that, InfoVis methods are often used to get an overview of an area without a specific goal in mind [2].

Unluckily, there is still no clear-cut and commonly accepted definition of the term "insight" [40]. North [23] argues that insights are complex, deep, qualitative, unexpected and relevant. Yi et al. [40] point out that the process of insight generation is

often related to an iterative process of sensemaking including not only discovery but also generation of meaning.

Exploration of data represented by InfoVis methods is to a certain extent a problem-solving activity [14]. Gestalt psychologists, for example, describe problem solving as a form of behavior "characterized by insight into the structure of the problem and by productive restructurings of the problem" [9, p.371]. Insights can occur unexpectedly when the underlying structure of the issue at hand is suddenly perceived. This description has some similarity with the term insight as it is used for InfoVis evaluation. Mayer [21] describes several different views of the concept of insight based on the assumptions of Gestalt psychology. The idea of insight as suddenly reorganizing visual information and insight as the reformulation of a problem seem to be especially relevant for information visualization. In information visualization, the reorganization of visual information can be supported by multiple views, zooming, panning, filtering and similar means. This does not imply, however, that the usage of these features automatically leads to insight generation, but they may help to build new mental models of the problem at hand. Insight as reformulation of a problem implies that the structure of a problem plays an important role for finding a solution. When things "fall into place" the correct structure can be perceived. This structure can also be represented by InfoVis methodologies.

There is some consensus that Gestalt psychology outlined very interesting research questions. It should be mentioned, however, that their investigations did not follow rigorous principles for scientific experiments and that their definition of the concept of 'insight' remains quite vague [9]. In recent years, more rigorous experimentation has taken place to clarify this concept (see e.g., [24, 7]). This research might form a framework for research on insight in information visualization.

The term insight as it is used in the evaluation of InfoVis methods is related to the concept of exploration. It is usually assumed that exploration is necessary for gaining insights. This approach is also supported by current research in the psychology of perception. Researchers have repeatedly pointed out that perception is exploratory in nature [28, 37]. Ware [36, 37] describes perception as visual queries. Visual queries search for patterns in the world outside. This capacity of human information processing is very flexible and adaptive. The view that human vision is active is also supported by other psychologists studying perception (see e.g., [11, 12]). Rensink [28] points out that the dependency of visual perception on the environment as a kind of external memory makes it fairly natural to design visualizations specifically to support such processes.

The notion that the exploration of visualized data leads to insights also implies that alternative methods of evaluations have to be used apart from measuring time and error [3, 4]. North [23] emphasizes that it is difficult to evaluate the quality and effectiveness of a complex InfoVis tool with quantitative methods. Alternative methods of evaluation are necessary to capture the strengths and weaknesses of such tools. Fekete et al. [10] point out that it is challenging to measure insights and to evaluate the benefits of InfoVis methods. The exploratory nature of searching for information with the aid of InfoVis methods makes this evaluation process especially difficult. The dynamic character of these search activities requires specific methodologies to capture the progress of human reasoning processes. One of these

methodologies to investigate the sequence of the users' actions is software logging. Kang et al [18] describe such an investigation which differs from our approach insofar as the only activities they consider are observations of different views of a multiple view system, whereas we study practically all actions carried out while interacting with an information visualization. Similar approaches were also used by Cowley et al [6], Dou et al [8] and Shrinivasan and van Wijk [35] who adopted software logging for providing histories of usage. These systems could, in some cases, be used for the investigation of reasoning processes, but their main aim is to support different user groups in their work and provide them with a collection of recent search results and indications of how these results were arrived at. The case studies provided by Shrinivasan and van Wijk [35] are very interesting, but on a more general level than our investigation.

All these approaches informed our research and the hypotheses we investigated.

3. GRAVI++

The interactive InfoVis method Gravi++ was designed to support therapists in their analysis of the development of anorectic young women during psychotherapy [15]. It was developed to find interdependencies between various kinds of parameters relevant for the success or failure of the therapy (especially questionnaire variables like depression or self-efficacy). There are two kinds of icons, one representing patients and the other questionnaires. The questionnaire icons are situated at the border of the representation and the patients' icons are in the middle. Every patient icon is attracted by the various questionnaire icons according to the score derived from the answers this patient gave. The visualization is based on a spring metaphor and leads to the formation of clusters of persons who gave similar answers. Morse and Lewis [22] describe a similar approach. It should be mentioned, however, that Gravi++ is more interactive than the tool described by Morse and Lewis and also offers alternative methods of visualization. Another very similar approach is Dust and Magnet which uses different visual cues and animation strategies than Gravi++ [38].

The color of a patient icon corresponds to a classification of the therapy outcome done by the therapist: red (negative outcome), green (positive outcome), blue (drop out), gray (not yet classified – currently in therapy). The users can choose which questionnaire icons and which patient icons are shown in the visualization. There are different methods to achieve this (menu, drag&drop). These icons can also be hidden when they are not needed anymore. In addition, the questionnaire icons can be moved around on the screen. A consequence of this can be that the clusters of patients with negative and positive therapy outcomes become more distinct (leading to a high quality configuration of icons on the screen).

To visualize the development of the patients during the therapy, Gravi++ uses animation. The position of each patients' icon moves according to the patients' values for the questionnaire items. There are data for five time steps (The same questionnaires were filled in before the therapy, three times during the therapy and one time after the therapy). Alternatively, the change over time can also be visualized by so-called Traces. Traces show the path the patients' icons take across the screen. To visualize the exact score of the patients on each questionnaire, rings around the questionnaire icon can be drawn. The rings' size corresponds to

the attraction of the patients' icon to the questionnaire (Attraction Fields). Another visualization method integrated into Gravi++ are Starglyphs. Figure 1 shows a screenshot of Gravi++ with all visualization options activated.
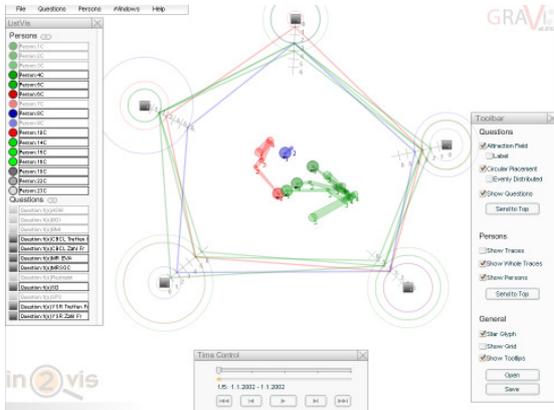

Figure 1. A screenshot of Gravi showing Attraction Fields, Starglyph, and Traces

The goal of Gravi++ is to explore time-oriented data and to identify predictors (that is, variables capable to predict the outcome of the therapy). The different methods of visualization (clusters of patients' icons, Attraction Fields, Starglyph, Traces, Animation) allow various views of the data. An additional form of interactivity is the possibility to choose which patients' and questionnaire icons should be used. The visualization options together with diverse other interaction possibilities indicate that there is not one optimal visualization configuration for any given question or hypothesis but many different views on the data.

4. DESCRIPTION OF THE INVESTIGATION

4.1 Sample
In this section we want to describe the setting of the investigation we conducted in the course of the "in2vis" project. It has often been suggested that it would be more advantageous to employ real users as subjects of an evaluation study of an InfoVis method [25]. Nevertheless, there are situations where this is not possible. We cooperate with two psychotherapists with marked time constraints. Extensive testing is, therefore, not possible with our project partners. In addition, sample sizes are much bigger when university students are used which makes results more representative. So, we decided to use computer science students as subjects. The sample size was 32. These students got a one-hour instruction into the domain area (psychotherapy and the problems of anorectic young women) and another one into the InfoVis methodology (Gravi++). The actual testing itself took place in a computer laboratory at our university and lasted one hour. Previous results have been discussed elsewhere [30].

4.2 Scenarios
The tasks the subjects had to solve were exploratory in nature. The psychotherapists are especially interested in the variables influencing success or failure of the therapy (i.e. predictors). The

tasks were formulated in the form of scenarios which specified meaningful subsets of the data to explore (questionnaires, patients, time steps). The first scenario was: realize change over time of 16 patients in 5 dimensions (questionnaires) and identify positive and negative predictors. The second scenario was: recognize the consistent/inconsistent answers of parents and patients in the first time step and their role as a predictor. The scenarios were developed in cooperation with the therapists. The therapists also described what was a plausible insight into the data.

4.3 Software Logging
As mentioned above, new methodologies have to be found to analyze the users' explorative behavior. Time and error are not an issue in the case of Gravi++. In general, we would like to motivate the users to interact with Gravi++ for longer periods of time, therefore time spent on tasks is no indicator for the quality of the system. In addition, it is not possible to commit errors in the strict sense of word, although users might arrive at an implausible insight. We are rather interested in interaction patterns of the users and an analysis of the results of their exploration process than in time spent on tasks and errors. We chose software logging as methodology because it captures dynamic aspects of user behavior.

Software logging is not intrusive and can also be partly automated [27]. It yields data which can be used to analyze the interaction of the users with the InfoVis method. It is extensively used for the evaluation of Websites [19]. Ivory and Hearst [17] give a detailed overview of data capturing through logfiles and logfile analysis. They concentrate on logfile analysis to support usability testing. This is based on time and error as important variables. Often, a precise model of appropriate sequences of actions has to be developed before testing. Such an approach is not suitable in our context. We, therefore, developed our own program to analyze the logfiles and to help with the statistical evaluations. This program is written in Java. An important issue in analyzing the logfiles is the definition of what constitutes patterns in the behavior of the users. Schümmer et al. [34], e.g., developed an interesting metric for collaborative activities. Unluckily, it is not useful for our purposes as we do not deal with collaborative activities. Therefore, we propose our own solution for the definition of patterns which is adapted to specifics of interacting with InfoVis methodologies. We were mainly interested in how the user interacted with Gravi++, therefore the logfiles log only user interactions; activation/deactivation of the various visualization methods and how this was done (menu, toolbar), how and where to person and questionnaire icons (including the name of the icon) were moved, add and remove of icons and the method used (drag&drop, pull-down menu), activation/deactivation of the highlight function, use of the time function (including the specific time step), and when a tooltip was activated/deactivated. For every line in the logfile the system time and name of the workstation was logged.

The length of the logfiles for scenario A and B varies from user to user. The longest is 2476 lines the smallest 783 lines, the average is 1555 lines. The statistical analysis for the logfiles was conducted using SPSS.

During the analysis of the logfiles we discovered certain problems. Due to Gravi++'s design, tooltips activate as soon as the mouse pointer passes over an icon. Therefore it is sometimes difficult to find out whether it was always a conscious act of the user or not. A careful analysis of the logfiles indicates, however, that the vast majority of these activities were conscious acts.

4.4 Hypotheses

The goal of the research described in this paper was to get some tentative ideas about the activity patterns users adopt when they interact with InfoVis methodologies. We assume that these activity patterns are some indications for the underlying reasoning processes subjects adopt. The kind of activities subjects engage in, for example, or the successive order of such activities might give researchers information about the nature of these reasoning processes. It is obvious that such an analysis cannot be based on the results of the investigation of the usage of only one InfoVis methodology. We intend to conduct similar investigations with other methodologies in the future and compare them to this study. To do this, the adoption of a more general categorization system of activities is probably necessary to be able to compare results. Such a system of categorization has, for example, been suggested by Yi et al. [39].

The following hypotheses were tested in this study.

1. There are significant differences in the number of times various activities are performed. This would indicate that subjects think some of the activities are more useful for achieving their goal than others.

2. Users follow distinctive usage patterns when they interact with InfoVis methodologies. This would indicate that they do not interact with such methodologies in a haphazard way choosing activities more or less randomly but follow a systematic strategy.

3. Such usage patterns are adopted by most of the subjects in a similar way.

4. Different tasks afford different usage patterns. This means that specific activities will be used to a larger extent for solving one kind of problem and less for solving other kinds of problems.

5. RESULTS OF CURRENT RESEARCH

5.1 Activities

The aim of the study described in this section is to use dynamic data to analyze the exploratory processes the users engage in when they work with InfoVis methodologies. It has been argued that processes of insight generation might take a very long time [5]. Therefore, it is sometimes difficult to define the most important features of an InfoVis method for the generation of a specific insight. It is not necessarily the last view a user has seen which might influence him or her most. This is consistent with the views put forward by Gestalt psychology. Gestalt psychology posits that problem solving is, in general, a long process of restructuring the available information, until things fall into place and a solution is found. Sometimes, it seems to observers that people who solve problems move things about quite aimlessly. Such activity might still be crucial for finding solutions. Therefore, it is necessary to look at the whole process of generation of insights to find the most important factors. It must

be pointed out, however, that this is probably very difficult to achieve.

Table 1. Frequency of interactive activities

	Categori-zation [39]	Mean	Standard deviation
Starglyph show	Encode	4,74	4
Attraction Fields show	Encode	3,39	2,29
Traces show	Encode	7,97	5,28
P-Move	Reconfigure	39,94	36,76
Q-Move	Reconfigure	56,81	38,23
P-Add		37,48	34,71
P-Remove		26,39	28,19
Q-Add		20,29	8,37
Q-Remove		13,48	9,3
Time	(Explore)	188,19	113,51
Highlight	Select	33	40,16
P-Tooltip	Abstract/ Elaborate	342,71	166,8
Q-Tooltip	Abstract/ Elaborate	142,9	64,53

P... person, Q...question

The results of the software logging indicates that there are three different kinds of interactive behaviors. The first kind is characterized by a low mean and standard deviation, the third kind by a high mean and standard deviation, and the second kind is somewhere between the two. The first kind encompasses interaction with Attraction Fields, Starglyph and Traces, the second kind interaction with person icons and questionnaire icons. The third consists of the time function (animated time steps) and tooltips which show the exact data (see Table 1). The difference is probably systematic. The first group of interactions is related to interaction with visualization options, the second and third to interaction with data and the exact data. The second column in Table 1 categorizes the activities, where applicable, according to the categories of interaction proposed by Soo Yi et al. [39].

The software logging indicates that subjects prefer to interact with the data and do not experiment with the visualization options. The degree of interaction with the data is surprising in the case of adding or removing person and questionnaire icons because most scenarios suggested which persons and questionnaires should be analyzed. Nevertheless, the subjects experimented quite extensively with this feature. As mentioned above, some of the subjects only used a subset of the suggested persons and questionnaires. In many cases, this made sense and probably reduced complexity. People apparently also enjoyed moving questionnaire icons on the screen to get an advantageous configuration. It is noticeable that all these options could be used via drag&drop. Gravi++ also offers the possibility to add and remove person and questionnaire icons by menu options. This option was almost never used. Interacting with some of the visualization options made it necessary to use a menu. It might be

that people prefer to use drag&drop when they interact with InfoVis methods.

We did not expect subjects to look at the exact data to that extent. The time function is mostly used in combination with some other activity (see section 5.2).

There is no significant difference in the usage of Attraction Fields, Traces and Starglyphs (see Table 1). This seems to indicate that users choose their preferred method of visualization early on and do not experiment with these options very much. Originally, we assumed that subjects tried out the different options and formed their insights based on several different representations on the screen.

The various activities shown in table 1 can be interpreted according to a theory of problem solving inspired by Gestalt psychology. Gestalt psychology indicates that restructuring mental representations of problems is very important. Davidson [7] developed a framework of three processes that are vital for restructuring such representations. Two of these processes are essential for the interaction with information visualizations: selective encoding (finding an element which was not obvious previously) and selective combination (detecting a previously unobvious framework for features of the problem situation). Activities like tooltip, highlight, p-add and q-add can be seen as selective encoding, whereas time, p-move, q-move, starglyph show etc. can be interpreted as selective combination. This might indicate that selective combination occurs less often than selective encoding. This is only a tentative result for one InfoVis methodology and should be compared to the results concerning other InfoVis tools. It is also an open question what this means for the quality of the insights gained by InfoVis methodologies. It should be pointed out in this context that adoption of these activities does not automatically imply that mental images are restructured and insights gained. More research concerning these questions is necessary to clarify these issues.
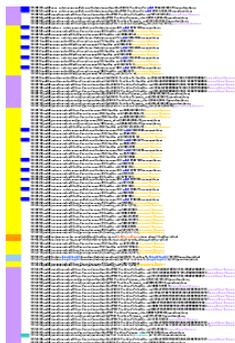
Figure 2. Part of a logfile and corresponding blocks

5.2 Interaction Patterns

Using a statistical analysis does not show strategies and patterns subjects used to solve the tasks. Therefore we conducted an in-depth analysis of the logfiles and looked at each logfile individually. This yielded some surprising results. Contrary to our belief that subjects would follow no particular pattern and use the visualization methods randomly, we discovered similar strategies and patterns that all subjects applied to solve the tasks. When we analyzed them, we found sequences of actions (blocks) in the logfiles. Figure 2 shows some lines from a logfile and the corresponding blocks.

There is one basic strategy that all subjects followed to some degree: add person and questionnaire icons, try visualization methods and decide on one, use the time/highlight function (note: the second scenario did not ask for the use of the time function). The subjects used tooltips (opened when the mouse pointer hovers over a person or questionnaire icon) to look at the actual data quite often throughout the tasks.

We paid special attention to the following user activities, which can be grouped into blocks.

time	use of the time control
hover	tooltip; separately for person and questionnaire icons
add	add person or questionnaire icons
remove	remove person or questionnaire icons
highlight	highlight person or questionnaire icons
visu	visualization method (Attraction Fields, Starglyph, Traces)
drag	moving person or questionnaire icons

Following are some examples of blocks we found (note: a block might also consist of only one activity e.g. "hover").

hover-drag	looking at tooltips and moving icons
add-remove-hover	looking at tooltips and adding or removing icons
time-hover-drag	using the time control, looking at tooltips and moving icons
time-visu-hover	using the time control, visualizations and tooltips
time-add-remove-hover-drag	using the time control, looking at tooltips and removing/adding/moving icons
highlight-hover	using highlight and tooltip

Figure 3 shows some examples of typical blocks. We searched for large blocks consisting of repeated activity sequences to facilitate the comparison between subjects and to see larger patterns. Those large blocks like "time-add-remove-hover-drag" might actually have sub blocks of "add-remove-hover". This kind of task-interlacing is very common. Single activities with no connection to the surrounding activities, were considered to be random user activities and were ignored. Starting and ending points of large blocks are often not easy to define. In such cases we took a closer look at the logfile data (e.g. which specific persons did the subject look at) to help us decide where to set the start and ending points of a block.
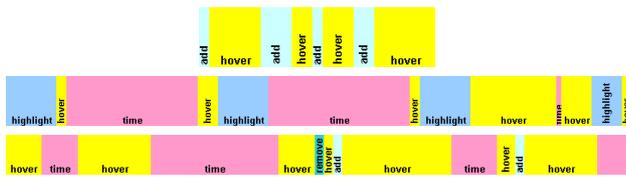
Figure 3. "add-hover" (top), "time-highlight-hover" (middle) and "time-add-remove-hover-drag" (bottom) blocks. Activities are color coded. Different colors characterize different activities. The length of a square shows the number of activities this square represents.

The activities used most often were "time" and "hover". The second scenario did not explicitly ask for the use of the time function, but twenty-four subjects still used it at least once even though data was only available for time step one, four, and five. "Time" was mostly used in connection with another activity ("hover", "add", "remove", "highlight") and is mostly a part of larger blocks. One subject didn't use "time" at all for scenario A, but used "highlight" and "drag" very often. "Hover" was often used in combination with "add" and "remove" actions.

Usually block sizes range from only a few lines in the logfile to about two hundred. One subject used the time function after every change of the visualization method, "highlight", "add" and "remove" which lead to a block consisting of 785 lines.

A minority of subjects did experiment with different visualizations. They activated them, but surprisingly often deactivated them again right after. The interval was sometimes only one or two seconds.

We analyzed why logfiles differ so much in length and discovered that this is due to the use of the tooltip function and time function.

Our research focused on low-level log files, but we hope to expand it in the future. Related research by Kang et al [18] and Gotz et al [13] might be helpful. As mentioned, Kang et al [18] investigated the sequence of users' actions and identified investigative strategies. Those strategies are OFD (Overview, Filter, and Detail), BFD (Build from Detail), HTK (Hit the Keyword), and FCFT (Find a Clue, Follow the Trail). Gotz et al [13] studied insight provenance. They define four tiers (events (e.g. mouse click), actions (e.g. filter), sub-tasks, tasks) to capture user behavior. Those tiers are from low-level to high-level and the represented actions also includes the users' intents. They also define sequences of actions (trails) that users use to accomplish sub-tasks. Various approaches with different InfoVis methodologies have to be compared to find out whether there are generic strategies users adopt to find solutions or whether these strategies depend on the specific InfoVis methodology used.

5.3 Analysis of Variance

In our research, we are mainly concerned with interaction patterns of users of InfoVis methodologies. To clarify these issues, we also conducted a quantitative analysis of the logfile data. We used two-way analysis of variance with tasks and activities as the two independent variables. The variable "scenario" refers to the two different scenarios the users had to analyze. We wanted to find out whether interaction patterns depend on the nature of the task (scenario) that is to be fulfilled on the one hand and whether there

is a significant variation in the activities (action) adopted by the users (e.g. adoption of specific forms of visualization of the data or decisions about inclusion of persons or questionnaires in the visualization – see 5.1.). The question is whether these variables are related to the number of interactions the users carry out.

The results indicate that there is a significant difference between various activities and between the tasks. In the second task, less activities related to time-dependent data are accomplished (see Figure 4). This refers to the animated time steps (action 10 in Figure 4) as well as the traces (action 3 in Figure 4). This is not surprising, as the second scenario does not explicitly ask for the comparison of several time steps. It should be pointed out, however, that this is the only difference. Otherwise, the activities the subjects adopt are quite similar to the ones adopted in the first scenario. We would have assumed there to be more pronounced differences between the first and the second task, that is that the subjects would adapt their interaction strategies to the tasks to a larger extent. There is also a significant difference between the number of times various activities are carried out (see Table 1). A few activities seem to be conducted significantly more often than others. Subjects looked at the exact values of the patients (P-Tooltip, Q-Tooltip) and at the animated time steps (in the first scenario) very often. The reason for looking at the animated time steps so often might be that short-term memory of human beings is very restricted, and subjects made up for this restriction by going through the time steps again and again. Informal observation indicates that looking at the patients' exact values is quite an automatic activity, and subjects might not even be aware of the fact that they do this so often.
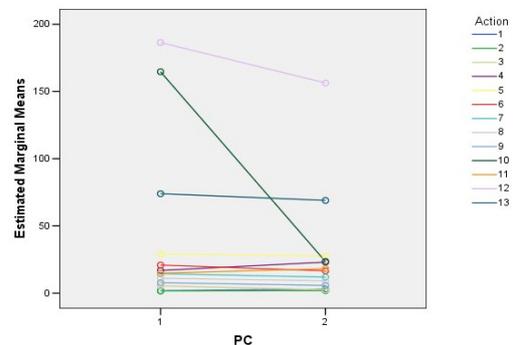

Figure 4. Estimated Marginal Means of Value

6. CONCLUSION

The investigation described in this paper tries to clarify how users explore data represented by a specific InfoVis methodology. The main study reported in this paper analyzes the results of software logging. The investigation indicates that users preferred animated time steps to Traces. Traces are possibly not easy to understand for the users. This is surprising as using animated time steps taxes short-term memory considerably. To overcome this limitation, subjects replayed the animated time steps again and again. Traces might be less attractive to users because of clutter on the screen. Other research also indicates that users' attitudes to Traces are sometimes ambiguous [31].

The main goal of the software logging study was to analyze interaction patterns. There were significant differences between

forms of interactions users engaged in when they worked with Gravi++. Users did not experiment with visualization methods to get different views of the data. On the other hand, getting information about the exact values of data points seemed to help them to get insights. They also replayed the animated time steps very often. These results are only valid for the usage of Gravi++, but we intend to compare them to research with other InfoVis methodologies in the future. In this context, we intend to adopt a more general system of categories of interactions with InfoVis methodologies (see e.g. Soo Yi et al. [39]) to be better able to compare results. There are also significant differences in interaction patterns concerning different tasks, although these differences are not as pronounced as we would have expected. Approaches in problem solving research inspired by Gestalt psychology might be used to interpret these results. Our investigation indicates that selective encoding occurs more often than selective combination. It is not clear whether this has negative consequences for the quality of insights. We intend to clarify this issue in the future and to conduct additional studies in this area with other InfoVis methodologies.

When analyzing the log files, distinct blocks of activities, that is systematic combination of single activities, could be observed. Users did not mix activities randomly when exploring Gravi++, but stuck to observable strategies. The activity blocks were quite similar across the sample. These results are more qualitative in nature. The activity blocks are quite obvious when one is looking at a visualization of the logfiles (see Figure 2), but it is difficult to describe them in quantitative terms because their boundaries are sometimes difficult to define. We intend to investigate such interaction patterns further with other InfoVis methodologies and we hope to develop more formalized methods of description of such blocks.

In future studies we would like to concentrate on defining investigative strategies users used to solve tasks and look at the users intents.

The research on exploratory behavior of users of InfoVis methods is still in its infancy. Nevertheless, we think that it might be valuable to investigate these issues because the results of this research might inform the design and development of such methods.

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