How Does Abundant Display Space Support Data Analysis?

Interaction Techniques for Information Visualizations on Large, High-Resolution Displays

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PhD thesis

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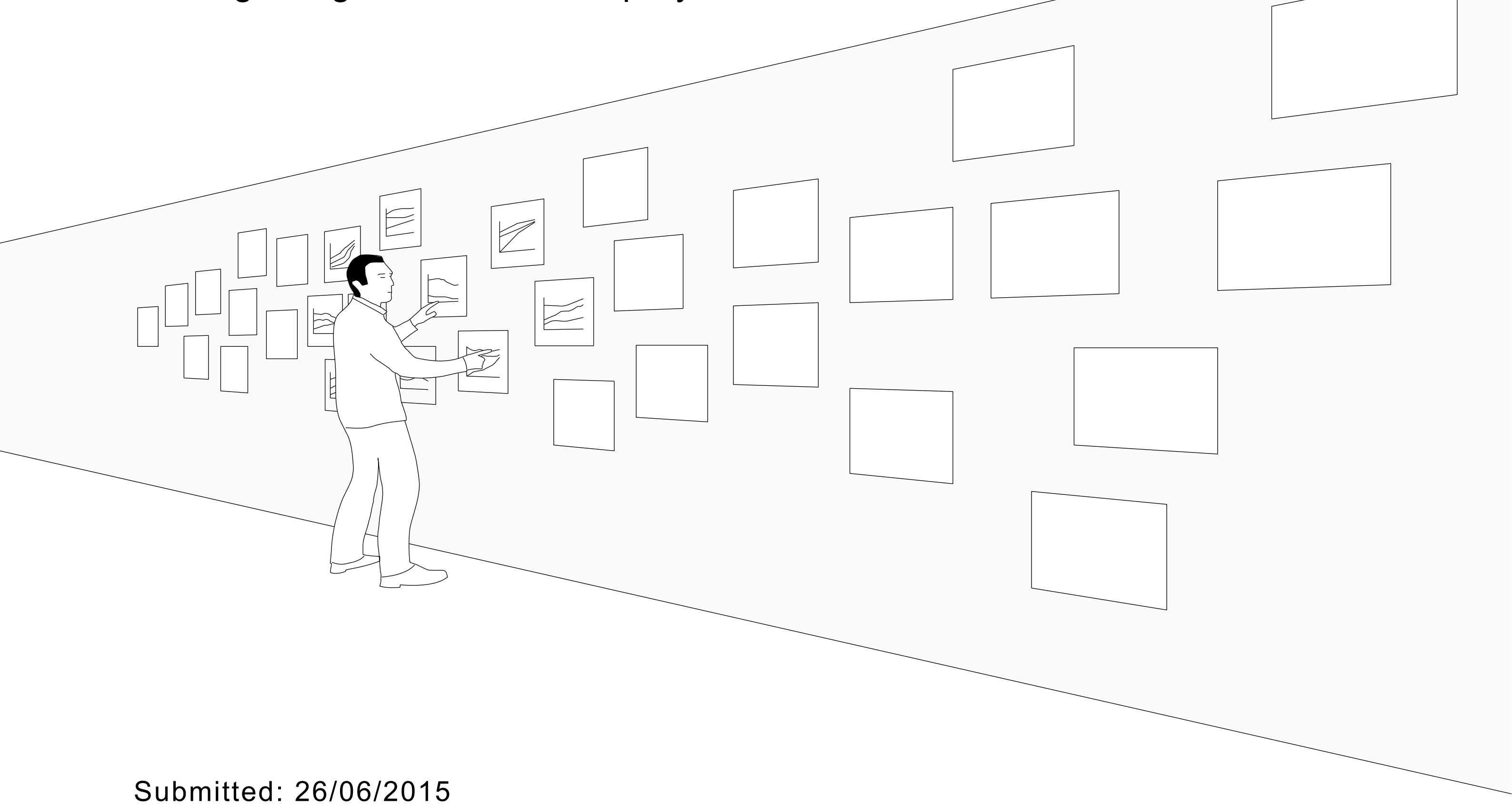

Submitted: 26/06/2015

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Title:	How does abundant display space support data analysis?
Subtitle:	Interaction techniques for information visualizations on large, high-resolution displays
Dansk titel:	Hvilke muligheder skaber ubegrænset plads for data analyse?
Dansk undertitel:	Interaktionsteknikker til informationsvisualiseringer på store skærme med høj opløsning.
Subject description:	Information Visualization (InfoVis); Human-Computer Interaction (HCI); Large, High-Resolution displays; Multi-touch; Touch; Proxemics; Data Analysis
Academic advisor:	Kasper Hornbæk
Submitted:	26. June 2015
Date of defence:	10. November 2015
Grade:	PhD

Abstract

Information visualizations on large, high-resolution displays (in the following, simply described as large displays) enable analysis of massive amounts of data by means of the sheer amount of pixels. Additionally, large displays with sufficient detail to enable close-up work provide what I define as *abundant display space*. Abundant display space allow people to organise visualizations and provide "space to think". Touch interactions might facilitate such organisation. The present thesis draws on the fields of human-computer interaction (HCI) and information visualization (InfoVis) to investigate the principal research question: How may abundant display space support visualization-based data analysis?

I base the thesis on four research papers:

In *Paper I*, we studied data analysis in a broad range of domains, and sought to answer how abundant display space may influence data analysis in these domains. We collected empirical data from eleven workshops with groups of two to three data analysts in varied domains (e.g., artistic photography, phone log analysis, astrophysics, and public health care analysis). We used grounded theory to analyse the collected data. From this, we identified six themes relating to the use of abundant display space. Most importantly, we identified themes that related to space and time. At one extreme, a visualization may take up an entire display. At the other extreme, many small visualizations may be organised spatially by people. Abundant display space may thus facilitate "space to think" with visualizations.

In *Paper II*, we studied the possibilities for combining information visualizations and interaction based on users' position and orientation. We conducted formative evaluations of three interfaces that compared these interaction possibilities to mouse based interaction with information visualizations on large displays.

In *Paper III*, we described F3, an interactive system for large touch displays. F3 provided interaction techniques that facilitate creating and combining visualizations based on an underlying data cube model. F3 visualized data from the Danish health care system. Specifically, the data described patient activities performed on approximately 50 hospitals, and described about twelve million patient contacts per year. We evaluated F3 in two user studies. The studies sought to (a) evaluate the system in terms of walk-up usability in a lab-based formative study, and (b) to evaluate the system in terms of real use, based on deploying F3 for two weeks with a group of health care analysts. The paper described the interaction techniques in F3 and reported findings from the studies based on interviews and observations data.

In *Paper IV*, we studied the diverse possibilities for showing relations between visualization views organised with the use of abundant display space. In particular, when many views are organised manually, it becomes necessary to support people in understanding the relations between the views. In the study, we conducted ten sessions with visualization and interaction experts that evaluated seven designs of visualization relations. In addition to evaluating our designs, participants sketched their own designs. A subsequent analysis based on grounded theory revealed a number of themes pertaining to showing relations. These findings, in combination with insights from the previous studies were used to describe a framework of visualization relations consisting of six dimensions.

In the final part of the thesis, I compare, contrast, and discuss the employed methodologies and findings from the four papers in terms of the principal research question.

Abstract (Danish)

Informationsvisualisering på store højopløsningsskærme muliggør visualisering af massive datamængder, særligt i kraft af antallet af pixels. Store højopløsningsskærme skærme giver i kraft af deres detaljegrad desuden mulighed for at interagere tæt på skærmen og giver hvad jeg kalder *oceaner af skærmplads*. Det giver mennesker mulighed for at organisere visualiseringer og "plads til at tænke", for eksempel ved hjælp af skærme med touch interaktion. Denne afhandling benytter forskningsfelterne menneske-maskine interaktion (HCI) og informationsvisualisering (InfoVis) for at undersøge hvordan *oceaner af skærmplads* kan give mulighed for at analysere data ved hjælp af visualiseringer.

Jeg baserer afhandlingen på fire videnskabelige artikler:

I artikel I undersøgte vi dataanalyse inden for en bred vifte af domæner, og sigtede mod at forstå hvordan *oceaner af skærmplads* kan anvendes til dataanalyse i disse domæner. Baseret på resultaterne af 11 workshops med grupper af to til tre analytikere i forskellige domæner (f.eks. kunstnerisk fotografi, log-analyse af telefonbrug, astrofysik, og analyse af data fra det offentlige sundhedssystem) identificerede vi seks temaer der relaterede sig til *oceaner af skærmplads*. Undersøgelsen ledte til en grundlæggende erkendelse af forholdet mellem skærmplads og størrelse på en eller flere visualiseringer: På den ene side, kan en visualisering fylde en hel skærm. På den anden side kan mange små visualiseringer organiseres spatialt af mennesker. *Oceaner af skærmplads* kan således give plads til at tænke med visualiseringer.

I *Artikel II* undersøgte vi kombination af informationsvisualisering og interaktion baseret på brugeres position og orientering. Vi afholdt formative evalueringer af tre grænseflader, og sammenlignede disse interaktionsmuligheder med muse-baseret interaktion på store højopløsningsskærme.

I Artikel III beskrev vi F3; et interaktivt system til store højopløsningsskærme. F3 anvendte interaktionsteknikker der giver mulighed for at danne og kombinere visualiseringer baseret på en underliggende datakube. F3 er designet og konstrueret til at kunne visualisere data fra det danske hospitalsvæsen der beskriver patientaktiviteter på omtrent 50 hospitaler og cirka 12 millioner patientkontakter årligt. Vi evaluerede F3 i to brugerundersøgelser der sigtede mod at (a) evaluere systemets umiddelbare brugervenlighed (walk-up usability) i en laboratoriebaseret formativ undersøgelse, og (b) evaluere systemet i regulær brug, baseret på at opstille F3 hos en gruppe der arbejder med at analysere data fra det danske hospitalsvæsen. Artiklen beskrev interaktionsteknikkerne i F3 og rapporterede indsigter fra undersøgelserne baseret på data fra interviews og observationer af brug.

I Artikel IV undersøgte vi muligheder for at vise relationer mellem visualiseringer. Det er nødvendigt når mange visualiseringer organiseres ved anvendelse af *oceaner af skærmplads*. Undersøgelsen baserede sig på ti sessioner med visualiserings- og interaktionseksperter, der evaluerede syv designs der viste relationer mellem visualiseringer. I tillæg til at evaluere vores designs, bad vi dem også om at skabe deres egne designs. Analyse af data fra sessionerne resulterede i en række temaer knyttet til visualiseringsrelationer. Disse temaer blev i kombination med resultater fra de tidligere studier brugt til at definere et metodeapparat (framework) for visualiseringsrelationer bestående af seks dimensioner.

Jeg afslutter afhandlingen med at diskutere de anvendte metoder og opnåede resultater i forhold til det grundlæggende forskningsspørgsmål. Jeg baserer dette på mine fire forskningsartikler.

Preface

This thesis is submitted to obtain the PhD degree at the Department of Computer Science, University of Copenhagen. The work described in the thesis was carried out between April 2011 and June 2015.

During my PhD, I had the pleasure of meeting many inspiring researchers, to which I am thankful. First, I want to thank my supervisor, Kasper Hornbæk, for insightful guidance and support. I also want to thank the members of the Human-Centered Computing group. I am grateful to have been a part of this group. I particularly want to thank Mikkel Rønne Jakobsen and Sebastian Boring for insightful discussions and valuable feedback along the way.

In the fall of 2013, I visited the Interactions Lab at Department of Computer Science, University of Calgary, Alberta, Canada. In this connection, I want to thank Professor Sheelagh Carpendale. First, for her kind and insightful guidance and for showing me a new perspective on communicating and discussing research. Secondly, for inviting me to be a part of her great group of scholars. I owe thanks to the kind and friendly members of this group, and other members of the Interactions Lab, who made my stay in Calgary a great academic as well as social experience.

I also want to thank the many people who participated in the studies I conducted. I particularly want to thank the many analysts at the State Serum Institute. Without you, this thesis would not exist.

I have found two abilities to be important to staying sane in academia. First, being able to say goodbye is a crucial ability. During my PhD, I have had the pleasure of meeting wonderful and inspiring people, many of which I have also had to say goodbye to. Second, it is important to be able to receive and acknowledge rejections, to keep moving forward, and not (always) to take no for an answer. Rejections are part of academia. Stubbornness is mandatory.

I am eternally grateful for the love, support, and acceptance from my wife and son. I have spent countless evenings in the lab and sung a myriad of lullabies carried through radio waves. Thank you for missing me. I cannot wait to spend more time with you.

Søren Knudsen
Copenhagen, June 2015

List of papers

I **Knudsen, S.**, Jakobsen, M. R., Hornbæk, K. 2012. An exploratory study of how abundant display space may support data analysis. In *Proceedings of the 7th Nordic Conference on Human-Computer Interaction: Making Sense Through Design (NordiCHI '12)*. ACM, New York, NY, USA, 558-567.

II Jakobsen, M. R., Haile, Y. S., **Knudsen, S.**, Hornbæk, K. 2013. Information Visualization and Proxemics: Design Opportunities and Empirical Findings. In *IEEE Transactions on Visualization and Computer Graphics*. vol. 19, no. 12, Dec. 2013.

III **Knudsen, S.**, Hornbæk, K. 2014. F3: Fast, Fluid, and Flexible Data Analysis on Large and High-Resolution Touch Displays. In preparation.

IV **Knudsen, S**., Carpendale, S. 2014. Representing View Relations: A Qualitative Study on Between-View Meta-Visualizations. In preparation.

Contents

Part I
Introduction

Chapter 1
Introduction

In the last decades, the amount of collected data have risen to levels beyond comprehension, spanning data that describe peoples' wellbeing, objects' whereabouts, and organisations' activities (e.g., in health care). It is, for example estimated that the Internet alone consisted of around 4.4 Zettabytes in 2013 [149]. In short, we are stockpiling data under the assumption that emerging tools and technology will add value to all this data.

There is a clear need for humans to understand data. In this chapter, I first introduce data analysis, and subsequently visualizations as a method to gain knowledge of and understand data. Second, I present arguments for supporting this need grounded in the information visualization field. In the next chapter, I describe work that relates to my contributions.

Humans analyse data to gain knowledge. In this thesis, I use the term data analysis in a broad sense to denote gathering, organizing, reading, extracting, visualizing, checking, and narrating data. It is related to sensemaking [119] as well as to the types of activity supported in visual analytics [142]. At a higher level, data analysis includes the generation of hypotheses from data, discovery of new insights in data, and looking through data to understand the distribution of certain characteristics [21, 148].

Computer Science is, at its root, concerned with processing and analysing data. By processing data, computers help gain knowledge of observed phenomena. Since the 1960'ies, computers have advanced humans' abilities to collect and comprehend information. Thus, computers might support a broad range of activities related to data analysis.

However, no tool or technology can carry out data analysis in isolation. We as humans must add value to the data, through generating insights, and making more informed, and hopefully wiser decisions. The amount and complexity of data often makes that a challenging task, necessitating both useable, useful, and effective tools and techniques.

Visualization is such a technique. Visualizations help people understand data and make decisions, and has been an effective tool for generating insights, and further understanding of phenomena for centuries [47]. William Playfair's time-series graph of prices, wages, and reigning ruler over a 250-year period and Dr John Snow's dot Cholera map are examples of early visualizations, which highlight the cognitive benefits of visualizations. In the recent decades, computer visualizations have been successfully applied to numerous disciplines. Computer tools allow rapid generation of visualizations and in addition, allow for interactivity, which further supports peoples' cognition.

A specific set of visualization techniques are known as information visualizations, and concern the visualization of abstract data. This area has been defined as "the idea of using computer-supported, interactive, visual representations of abstract data to amplify cognition" [25]. Dissecting this definition, three important aspects emerge: (1) Interaction, (2) visual representations, and (3) cognition. Information visualization concern the idea that we, as humans, through interacting with and inquiring about visual representations can obtain a higher degree of understanding (i.e., cognition). The role of interaction and inquiry and its relationship to visual representations is not well understood, although it is acknowledged as an important role in data analysis [110, 142, 164].

1.1 Research question

To show visualizations, classic visualization techniques have relied on displays in common use for desktop and laptop computers. Recently, large, vertical, high-resolution displays (in the following described as large displays) have emerged. These displays might provide people sufficient display space for all practical purposes, and thus give people a sense of display space abundance. This is the core idea of my research. Thus the central research question guiding this thesis has been:

> *How may abundant display space support visualization-based data analysis?*

With abundant display space (e.g., provided by large displays), people are free to move around and thus less restricted to desks and typical interaction devices (i.e., mouse and keyboard). This however, implies that such devices are insufficient with abundant display space, and thus necessitates alternative and novel input technologies, interaction techniques, and modalities. A large body of my work thus focus on providing novel interaction techniques for information visualizations. In my work, I have used qualitative methods to explore and cast light on if, how and when the studied technologies may help gain knowledge of and understand data.

1.2 Thesis overview

The remaining parts of the thesis are structured as follows:

Part I comprises this chapter and Chapter 2. In Chapter 2, I outline related work on combining information visualizations with novel interaction techniques for emerging user interface technologies.

Part II comprises Chapter 3 to 7. In this part, I describe my contributions to this area through four paper contributions.

Part III comprises Chapter 8 and 9. In Chapter 8, I discuss and contrast the contributions and the chosen methodology. Finally, in Chapter 9, I conclude the thesis and point to opportunities for future work.

Chapter 2
Overview of related work

My thesis work concerns information visualizations (InfoVis) on large, high-resolution displays (in the following described as large displays), driven by novel interaction techniques. In this chapter, I give an overview of related work in these areas.

I structure this chapter as follows: First, I describe combinations of touch and movement with information visualizations. This focuses on interaction. Secondly, I describe combinations of information visualization and a novel display technology, in the form of large displays. This focuses on visual representations.

2.1 Combining touch and movement with information visualizations

Much research have studied mouse and keyboard interaction for information visualizations. However, numerous alternative input devices exist. For example, touch interaction, mid-air interaction, location tracking, presence detection, tangible interaction, and speech interaction. However, research on information visualizations driven by novel input technologies are scarce [90]. Novel input technologies may provide more degrees-of-freedom, and thus potentially provide better mapping between action and intent [12], and reduce the number of necessary user interface components. Input technologies may additionally detect for example proxemics [58] and use these to direct implicit and explicit interaction techniques [9]. In addition, novel gesture-based interaction techniques may allow for more “natural” interactions [57, 159], which are inspired by how people use their body for everyday tasks and reduce the gap between people and technology [90], for example through embodiment. Novel input technologies may also offer device-less and hands-free interactions, which enable new contexts of use for InfoVis such as in meeting rooms (e.g., [22, 157]), museums (e.g., [63, 96]) and other public places.

It is therefore relevant to understand how we might use these novel technologies for interacting with information visualizations, and how we might design interaction techniques for them. In the following, I describe contributions that sought to study interaction with information visualizations. First, I describe contributions that consider touch interaction. Secondly, I describe contributions that consider movement and location of people.

2.1.1 Touch

A limited number of studies combine touch interaction and information visualization [90, 115]. However, the area seems to gain attention.

The amount of research on general touch interaction in HCI necessitates narrowing the scope. Specifically, I leave out the following:

- Gestural touch interaction. A large body of work exists on gestural touch interaction. In particular: Gesture design and design methodology (e.g., [161, 163]); detection (e.g., [81, 160]), use (e.g., [63]); performance (e.g., [65]); end-user customization (e.g., [108]); size (e.g., [94, 150]); learnability and memorability (e.g., [1, 102]); naturalness (e.g., [51]); and handedness (e.g., [6]). The broad scope of these works makes it difficult to provide a proper description of the terms' use. In the following, I describe what related work has referred to as gestural interaction. However, my focus and description rely on the specific ways that people use fingers and hands as part of interactions.
- Much of the early work that combined touch interaction techniques and information visualization contributions focused on the novel possibilities afforded by horizontal displays. These particularly studied co-located collaboration and the use of space (e.g., [69, 124, 143]). While these are interesting in relation to this thesis, they have little relevance in touch input and interaction techniques. Therefore, I return to these in the following section on large displays.

In the following subsections, I thus outline existing contributions that combine touch interaction and information visualization. I do this by considering the possible ways that touch might drive information visualizations. I describe this first in terms of interacting directly with data points (i.e., touching data). Subsequently, I describe interaction techniques, by using the concept of interaction instruments [12]. I then describe approaches to design and evaluate touch interaction techniques, and the visualization tasks these techniques support.

2.1.2 Touching data

The subsection title t*ouching data* refers to studying how people might interact directly with visualized data using touch input. With touch input, designers can create interaction techniques that allows users to be in direct contact with data points. The following considers this aspect, which has particular relevance in relation to information visualization.

North, Dwyer, et al. [107] studied people interacting with a tabletop interface before or after exposure to one of two other interfaces: Mouse and physical. Thus, they divided participants in four groups. Participants that initially used the physical interface (PS condition) finished tasks faster when they later used the tabletop interface to perform similar tasks, than participants initially used the mouse interface (MS condition). Interestingly, participants' choice of strategy underlined this finding, for example in that PS participants were more likely to use multiple fingers in the tabletop interface, than MS participants. This suggests the designed (and potentially in general) touch interaction techniques mimicked the physical world more closely than the mouse interaction techniques. Additionally, it might suggest that this mimicry might not work well in situations where people expect, or are used to, mouse interactions.

In a later paper, Dwyer, North et al. [38] described how participants (in the same study) laid out graphs (a separate user task in the study) in the mouse and tabletop interfaces. The authors noted that the tabletop interface encouraged *touch-thinking* (i.e., "thinking with the hands") as "suggested by the principles of embodied interaction" [35]. Participants that used on average 277 touches to move nodes about 240 times in the tabletop condition, used on average of 103 mouse clicks to move nodes 117 times. On average, the participants spent approximately the same time with the two interfaces. The authors explained that participants made minor adjustments exclusively in the tabletop condition.

Tabletop displays supports two-handed input, but interaction techniques that leverage these possibilities for information visualization are scarce. Dwyer, North et al. [38] saw a decrease in the use of multi-touch interaction in mentally demanding tasks. This stands in contrast to a 1999 study by Leganchuk et al. [92]. This study showed improved performance for bimanual techniques over one-handed techniques. Moreover, the study improvements increased for mentally demanding tasks. Perhaps, the discrepancies are due to the nature of the tasks. In the study by Leganchuk et al., the bi-manual interaction techniques were based on Guiard's kinematic chain model, whereas the study by Dwyer, North et al. compared the relative number of contact points for a simple and a complex task (sorting and graph layout task). These differences potentially makes the findings incomparable. Perhaps interaction techniques tailored for two hands might benefit cognitively demanding tasks, whereas performing two simple tasks in parallel might not.

The notion of touch-thinking suggests that merely touching a data point should have little impact and be easily reversible [40]. This seems to be considered in TouchWave [10], that when touching the background, show details for streamgraph layers in an overlay. The overlay shows the value for

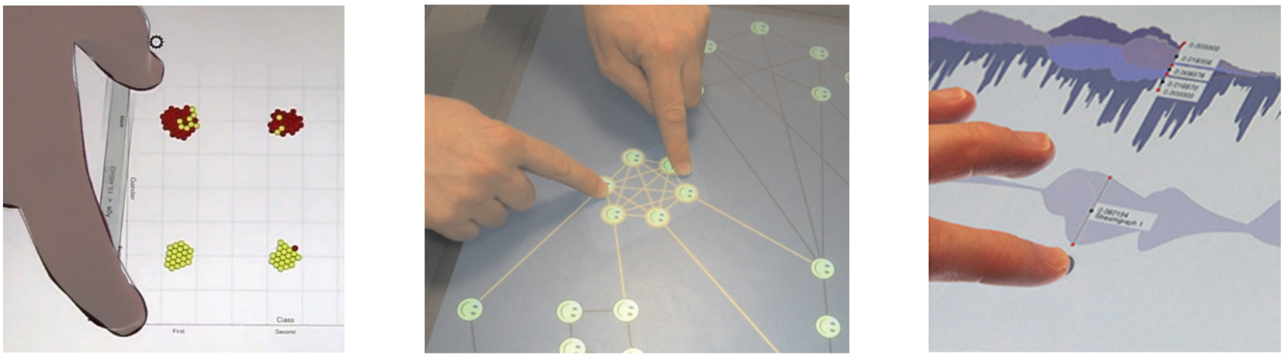


Figure 2.1: Left: Rzeszotarski & Kittur's [120] sieve metaphor for filtering. Center: Dwyer, North et al. [38] showed a convex hull based on multiple fingers. Two-finger interactions allowed affine transformations; Right: Baur et al. [10] showed values for horizontal positions in stream graphs by touching the background.

the horizontal positions of touch points. Figure 2.1c shows one of TouchWave's interaction techniques. This is comparable to interaction techniques that provide additional details by hovering a mouse pointer (e.g., [152]), which cannot be transferred directly to touch interactions techniques [159].

In designing touch interaction techniques for scatterplots, Sadana & Stasko [122] considered alternative interaction techniques for point selection. Data selection, particularly in scatterplots, demonstrates the fat finger problem (e.g., [155]). However, the authors ignore the potentially simplest solution, which is to select data points below a finger's position. Although the authors suggest that no ideal solution exists, they do note that many interaction techniques for minimizing the problem has been suggested (e.g., [13, 66, 99, 155]). In continuation of the point above, they ignore the issue of target loss caused by pointing or touch-thinking.

2.1.3 Touch interaction techniques

Where the above focused on touching data points explicitly, I now turn to consider more complex touch interaction techniques. In contrast to the simple interactions where a touch point corresponds to a single data point selection, these interaction techniques rely on intermediate tools to interact with a system, such as on-screen menus (e.g., in WIMP interfaces) and marking menus [87] (e.g., in post-WIMP [32] interfaces).

To describe these interaction techniques, the *instrumental interaction* [12] model may be used to illustrate how interactions may be designed around the use of instruments as mediators of action on domain objects. Based on this model, the interaction techniques described by Dwyer, North et al. [38], let multiple fingers form a convex hull (the instrument). Figure 2.1b shows parts of their design. Data points (the domain objects) within the hull were the object of the interaction. The data points moved when manipulating the hull with affine transformations. The interaction lasted until all fingers were released. This was an example of a technique that had a low degree of indirection, both in terms of spatial and temporal offset. The interaction on the instrument was performed almost at the same position and at the same time, as the data points (domain objects) were moved.

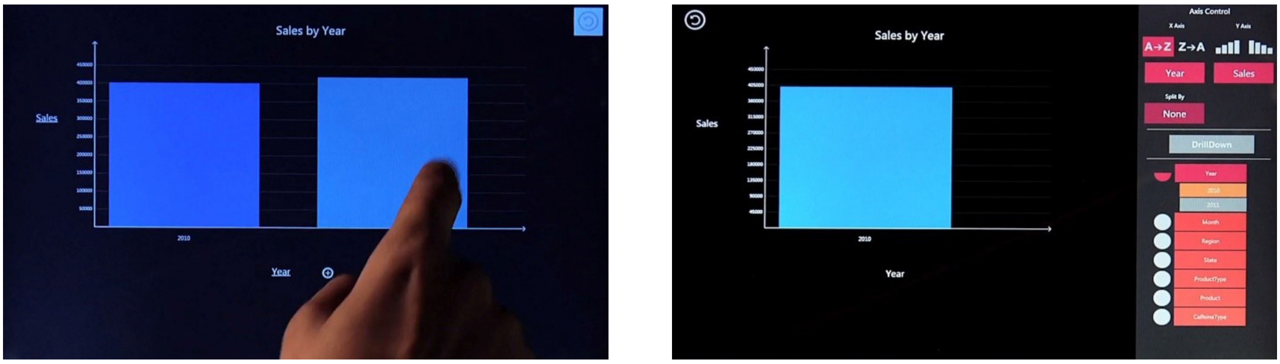


Figure 2.2: TouchViz by Drucker et al. [36] compared two user interfaces. In one interface (shown left), interaction was provided by interaction techniques based on Post-WIMP interaction concepts. To filter data, participants dragged down on a bar chart. In the other interface (shown right), interaction mimicked WIMP interaction. To filter data, participants tapped menu items to the right of the bar chart.

In contrast to the very direct graph interaction, Rzeszotarski & Kittur designed a filter that used a sieve metaphor for Kinetica [120]. Figure 2.1a shows the sieve filter. Dragging a sieve through a set of data points would filter away the data points matching the sieve. Focus on the interaction shifted from the objects of interest (the data points), to the sieve. The design of the technique resulted in a spatial offset between the interaction and the domain objects, while the temporal offset was kept low. The spatial offset, while resulting in some indirection, had the added benefit of enabling people to see the data points while they filtered the data, and so reduced the “fat finger” problem. Rzeszotarski & Kittur also contributed an inspiring metaphor of interaction based on kinetics. However, their work is outside the scope of this overview, due to its negligible relevance to touch.

Drucker et al. [6] compared two sets of interaction techniques for interacting with bar charts (see Figure 2.2). They based the first set of interaction techniques on a menu system inspired by WIMP interfaces (designated WIMP). In designing the second set of interaction techniques, the authors aimed for more direct, and fluid interaction (designated FLUID). Like North, Dwyer et al, they also considered direct interactions with domain objects (here domain objects take the form of data bars that represent aggregate data values). For example, flick down on a data bar to exclude the data, flick up to exclude all other data, and drag on an axis to sort relative to the direction of the drag.

In TouchWave, Baur et al. [10] aimed to provide kinetic interactions for stacked area charts. Their interaction techniques relied exclusively on direct manipulations on the streamgraphs. For example, to show a vertical ruler for horizontal touch location, drag a layer in a streamgraph to extract it, or two finger pinch to distort the global horizontal axis using the focus+context technique. They considered TouchWave’s modeless interaction techniques to be particularly valuable. They argued that the modeless interaction techniques were provided by “an interaction set that allowed every type of manipulation and measurement to be triggered at any time”. In contrast to this statement, they considered sub-layering, which they described as only showing sub-layers in a stacked graph of a certain size of stream, as an effective way to alleviate the fat finger problem. Although this technique does not qualify as a mode, it may present some of the same difficulties to people that use it.

The touch interaction techniques for scatterplots contributed by Sadana & Stasko [122] identified alternatives for selection, zooming, filtering, and configuring spatial encoding. Their work provided many designs for interacting with data through on-screen instruments. To zoom, they for example suggest pinching in the data area, pinching on axis, double tapping a highlighted axis range, pinching in data area to reveal a zoom lens, and finally double tapping data area to zoom to a predefined zoom level. Similar to Sadana & Stasko, Baur et al. [10] used zoom when individual layers were too small, for example, for a finger to hit it reliably.

Frisch et al. [49] elicited a set of interaction techniques for interacting with diagrams using pen and touch. The interaction techniques were defined by study participants and refined by experts (i.e. the authors). In the process, they identified two mental models for users' diagram interactions. In the first (*sketching*), users sketch parts of a diagram. In the second (*structural editing*), a higher level of abstraction was present both in the interaction and the intent (e.g., copy node). In addition, they reported that participants had no preference for either pen or touch. This led the authors to suggest to facilitate techniques with both input modalities when possible. For example, holding onto a node, while dragging with either touch or pen would copy it. Their focus was on creating and editing visual representations, and less on manipulating them with typical visualization techniques (e.g., filtering, highlighting and sorting).

Schmidt et al. [123] also contributed touch interaction techniques for node-link diagrams, although with a different focus. They provided interaction techniques for performing topology-based tasks such as finding adjacent nodes and shortest paths between nodes. They based some of the interaction techniques on previous node-link diagram interaction techniques for mouse input [162]. The authors argued that using multiple techniques simultaneously broadened the set of interaction possibilities, and felt more natural and straightforward than if restrained to an interface based on a single mouse pointer.

Walny et al. [157] studied pen and touch interactions in a Wizard of Oz study. Browne et al. [22] described SketchViz which were based on sketching interactions. Due to the lack of detailed descriptions of the touch interaction techniques in these contributions they are outside the scope of this section, and will be returned to in the next section on large displays.

Many of the interaction techniques described above have focused on using the space available on e.g., an iPad. While these are valuable contributions, they say little about using visualizations on larger devices. For example, it is evident from the contributions that they focus on a single visualization, and regard any other visual elements as menus. This is not necessarily true. In fact, it seems that the WIMP interface provided by Drucker et al. actually provided more than one visual representation of data. Aside from the bar chart (as reported by the authors), the WIMP interface showed a simple tree view to support filtering, which thus conveyed additional information about the data, as seen in Figure 2.2.

Few contributions have aimed to provide touch interactions for multiple visualizations. Vlaming et al. [153] created touch interactions that emulated mouse interactions for VisLink [29]. An informal user study suggested that participants did not perceive the provided touch interactions as emulating a mouse, but simply as touch interaction techniques. They also reported that participants used turn taking in interacting with the system instead of using it concurrently. Tobiaz et al. [143] also contributed touch for multiple visualizations. However, their focus was on collaborative work with information visualizations on large displays, and less on the interaction techniques. I return to this contribution later in the chapter, in relation to large displays.

2.1.4 Designing touch interaction techniques

Most InfoVis contributions that focus on touch input use experts to design interaction techniques (e.g., [10, 38, 107, 120, 122, 123, 153, 155]). Frisch et al. [49] is a notable exception. This stands in contrast to work in HCI (e.g., [108, 145, 161]), where several contributions have sought to elicit interaction techniques in user studies. In the InfoVis contributions described above, the authors have designed interaction techniques from design goals (e.g, [10]) or brainstorming with HCI practitioners (e.g., [36]).

The predominant approach to designing touch interactions for visualizations appear to be to first identify a visualization technique, then identify tasks to support, and finally, to map these tasks to interaction techniques. Baur et al. [10] for example used this design approach. They first identified a list of low-level tasks to support (i.e., *manipulate* tasks such as *select*, *arrange*, *navigate*). Then, they compiled two lists: the first list comprised all visual components (single layers, stacked graphs, background); the second list comprised all basic interactions (tap, drag, two-finger drag, etc.). Finally, they created a mapping between the visual components, the basic interactions, and the manipulation to occur.

Two papers describe a somewhat different approach. In Kinetica, Rzeszotarski & Kittur [120] used a metaphor of physical kinetics to generate different designs, for example the sieve described above. The authors then designed interaction techniques based on these metaphors. They describe how design, implementation, and evaluation (by the authors) were interspersed, reminding of agile software development. In TouchViz, Drucker et al. [36] first identified low-level *manipulate* tasks, second brainstormed interaction techniques for these tasks in collaboration with HCI practitioners, and third organised these techniques (e.g., reduced three filter techniques to one). Finally, they decided on the visualization technique to support.

Frisch et al. [48, 49] both relied on user participants in designing a set of interaction techniques for diagram editing, and later refined by experts (presumably the authors, does not specify). In refining the interaction techniques, the authors first stated goals for the refinement, primarily focused on keeping the value in the designs suggested by study participants. Secondly, they considered options to resolve conflicts in the user-elicited interaction techniques, which primarily were present because of lack of expressive power in the basic interactions. They considered to (a) add additional basic interactions, (b) introduce mode switches, (c) distinguish between input modalities (pen or touch), and (d) distinguish between basic interactions performed on different visual components. Finally, they settled on introducing an interactive border around nodes in the diagram.

In summary, the literature have used different approaches in the design of touch interaction techniques. Most commonly, experts have designed interaction techniques based on for example design goals and brainstorming sessions. In these situations, the design process been to: first, identify a visualization technique; second, identify tasks to support; and third, map these tasks to interaction techniques. Rzeszotarski & Kittur [120] and Drucker et al. [36] chose a slightly different approach. In contrast, Frisch et al. [48, 49] relied on a user study to design interaction techniques. Other visualization research have also relied on user studies (e.g., [157]), but have not provided refined interaction techniques. These have instead focused on guidelines and design implications.

Similar to the differences in design method, the tasks that researchers have aimed to support with touch interaction techniques have varied. I describe these variations in the next subsection.

2.1.5 Visualization tasks supported by touch interactions

In the previous sections, I described recent contributions in the area of touch interaction techniques for information visualizations. I will briefly discuss the range of supported visualization tasks in these based on Brehmer and Munzners' "multi-level typology of abstract visualization tasks" [21]. This typology serves to both discuss the goals, as well the low-level interactions that the interaction

Authors	Why (design goal)	Why (evaluation)	How
Sadana & Stasko [122]	Consume (discover) ► Search (explore)	No evaluation	Manipulate (select, navigate, arrange, change, filter)
Baur et al. [10]	Consume (discover, enjoy) ► Search (explore)	Consume (enjoy) ► Search (browse, explore) ► identify, compare (case data studies)	Manipulate (select, navigate, arrange, filter, aggregate)
Vlaming et al. [153]	Consume (discover) ► Search (explore)	Consume (discover) ► Search (lookup, browse, locate, explore) ► Query (identify, compare) (informal user study)	Manipulate (select, navigate, arrange, change, filter)
Drucker et al. [36]	Consume (discover) ► Search (explore)	Consume (discover) ► Search (browse, locate, explore) ► Query (identify, compare) (comparative user study)	Manipulate (select, navigate, filter, aggregate)
Rzeszotarski & Kittur [120]	Consume (discover) ► Search (browse, explore)	Consume (discover) ► Search (lookup, browse, locate, explore) ► Query (identify, compare, summarize) (comparative user study)	Encode, manipulate (select, navigate, arrange, change, filter, aggregate)
Dwyer, North et al. [38]	Produce	Produce (obs. study)	Manipulate (select, arrange)
North, Dwyer, et al. [107]	Produce	Produce (obs. study)	Manipulate (select, arrange)
Frisch et al. [49, 48]	Produce	Produce (gesture elicitation study)	Manipulate (select, navigate arrange, change, filter)
Schmidt et al. [123]	Consume (discover) ► Search (explore)	No evaluation	Manipulate (primarily select)
Voida et al. [155]	Consume (discover)	No evaluation	Manipulate (navigate)

Table 2.1: The why's and how's in Brehmer & Munzners' typology of visualization tasks for InfoVis contributions that focus on interaction techniques. Note that many of the contributions use *exploration* in the meaning of *discover* in the typology.

techniques support. Table 2.1 provides an overview of the contributions and the visualization tasks they aim to support in terms of the typology.

Seven of the papers stated an explicit goal of designing interaction techniques that support data exploration. For example, Rzeszotarski & Kittur [120] investigated "how post-WIMP interactions might improve exploratory data visualization". Similarly, Sadana & Stasko [122] "identified a set of interactive tasks/operations that supported exploration with scatterplots". Based on the contributions' goals, I found that the typology's word *discover* seem to map better to the goals stated. Therefore, I used this in Table 2.1.

Many papers that introduce novel interaction techniques for visualizations aim for an enjoyable experience. They argue for these goals based on post-WIMP interaction techniques and fluidity (e.g., [40, 90, 115]). This is also the case in the papers described above. For example, Baur et al. [10] describe an implicit goal of providing an enjoyable visualization experience, by describing the popularity and visual appeal of stacked area charts. For example, they refer to a New York Times' visualization, which used a stacked graph visualization to convey Movies' box office receipts.

I briefly described how research have considered visualization tasks in relation to touch interaction techniques. Interestingly, many of these contributions aim to support data exploration (e.g., [36, 122]) and aim for an enjoyable experience (e.g., [10]). This overview have shown that there is focus on the tasks supported by these contributions. Next, I describe how the contributions have evaluated whether the designs support the tasks they aimed to support.

2.1.6 Evaluations of touch interactions

Some InfoVis contributions that focus on touch input have elicited interaction techniques in user studies ([38, 48, 49, 107]). However, only few have conducted user evaluations of the interaction techniques they proposed ([36, 120]). The low number and quality of evaluations of touch interaction techniques is problematic. In Table 2.2, I provide an overview of the papers, their evaluation methodology, and the dataset used.

Authors	Evaluation type	Dataset
Sadana & Stasko [122]	None	Not described
Baur et al. [10]	Case data studies	Two months of personal music listening history and box office results of 52 movies over 80 weeks
Vlaming et al. [153]	Informal user study	No details (United Nations dataset)
Drucker et al. [36]	Comparative user study	4,248 and 16,798 rows (business operations)
Rzeszotarski & Kittur [120]	Comparative user study	73 rows (cereals), 133 rows (cars), 200 rows (people on board the Titanic)
Dwyer, North et al. [38]	None (observational study)	50 nodes, 75 links (no context)
North, Dwyer, et al. [107]	None (observational study)	200 coloured data points
Frisch et al. [48, 49]	None (gesture elicit. and refine studies)	Not applicable (diagram editing)
Schmidt et al. [123]	None	Not described
Voida et al. [155]	None	Not described

Table 2.2: contributions, evaluation methodology, and used dataset for papers that contribute touch interaction techniques.

Drucker et al. [36] aimed to study hedonic aspects of touch interaction techniques, stating a goal of understanding “whether, and how, the fluid, touch-based gesture interaction offers subjective or performance advantages over the current WIMP approach to data exploration on touch surfaces.” Subjective measures of *ease of use*, *ease of learning*, *speed*, and *efficiency* on a Likert scale were all higher for the FLUID condition than for the WIMP condition, and five participants volunteered that the FLUID interface was fun and engaging to use. However, Drucker et al. provided a poor match between the goal of the study (comparing WIMP and FLUID interactions), and the visualization tasks used in the study. In the study, participants were asked to solve *locate* and *browse* tasks, but not *explore* tasks. The tasks required participants to identify and, to some extent, compare information, but not to summarize information (e.g., to describe a relation between two attributes) or to *explore* the data set, to look for interesting information. In contrast, Rzeszotarski & Kittur [120] asked participants in their study few *locate* and *browse* tasks, in trade for open-ended *explore* tasks when using Kinetica. For example, they asked participants to pick a car based on the participants' own requirements, which they described before beginning the task. In a subsequent task, they asked participants to make as many findings in a dataset that contained a random sample of 200 passengers on the Titanic. The participants made descriptive, comparative, and summative findings in the dataset, which underlined the use of the interaction techniques.

A potential reason for the lack of user evaluation is that the advantages of touch input is still poorly understood, and our current methods of conducting evaluations are incapable of fully describing the perceived, but illusive benefits of touch interaction. Perhaps more contributions of touch interaction techniques for information visualization will include evaluations once the field is more established. Another explanation for the lack of user evaluations is that these types of evaluations are still somewhat rare in information visualization research [72].

The domains and datasets used in describing and evaluating the interaction techniques pose additional problems. First, the sizes of the used datasets are small, with the largest containing less than 20,000 rows. While many real-word datasets that people need to analyse fit this limitation, many are much larger. It is unclear how changes to the scale of datasets have impact on the use of interaction and visualization techniques. This potentially reduces the external validity of evaluations of any type.

The experience, knowledge, or work domain of participants may also play a role in user evaluations. Drucker et al. [36] discussed how the Post-WIMP interface helped to guide participants with seemingly low experience with data analysis towards solving tasks, because the amount of possibilities in configuring the bar chart visualization was low compared to the WIMP condition. In contrast, study participants with a more well founded analysis strategy seemed limited by the guiding provided in the Post-WIMP condition, and was more effective in the WIMP condition. This exemplifies the importance of the experience that participants bring with them to an experiment. For many evaluations, the experience have little importance. However, if domain experts will use a visualisation system, it is crucial to recruit participants from this domain, or with similar knowledge.

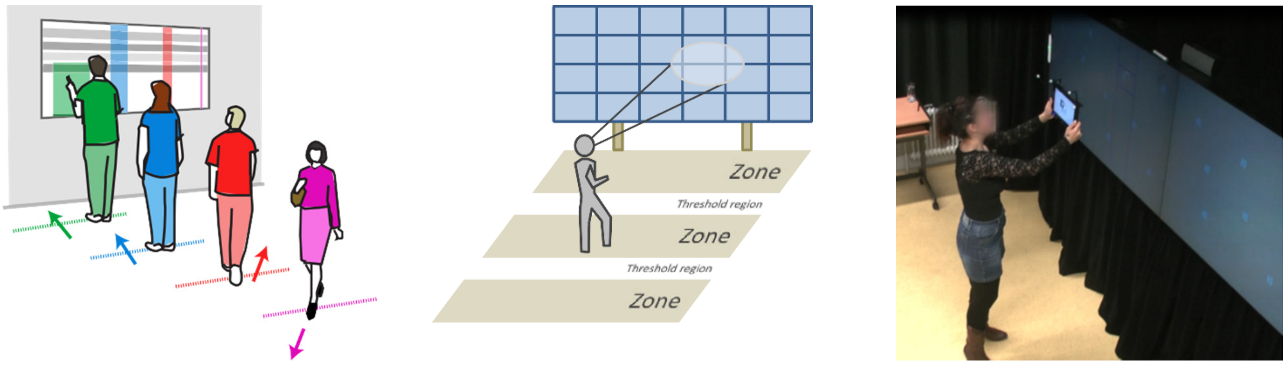


Figure 2.3: Interaction zones described by Vogel et al. [154] (left). Lens technique described by Lehmann et al. [93] (centre). Physical zoom-and-pan with tablet described by Rädle et al. [121] (right)

2.1.7 Summary of touch interaction

In the previous subsections, I have described contributions that studied touch interaction techniques for information visualizations. First, I described the benefits of direct manipulations for interacting with data points. Then, I gave an overview of papers that have contributed touch interaction techniques. Finally, I described how these contributions have approached design, task support, and evaluation.

In the next section, I briefly describe related work in using peoples' movement to drive interaction.

2.1.8 Use of peoples' movement for interaction

When people work in front of large displays, they might need to move to reach pertinent display areas. Additionally, interactive systems might react to peoples' implicit or explicit movements, thus changing display content. An example of an explicit interaction technique is to zoom a map, when a person approaches a display. Similarly, an example of an implicit interaction technique is to change the state of a visualization, when a person walks past the display. A few studies has investigated interaction with visualizations based on body movement, particularly in the context of large displays. Andrews et al. [2] provided an overview of potential interaction techniques for information visualizations on large displays.

A few interaction models exist that help understand and explore bodily interactions techniques. In addition to instrumental interaction, which I described and used in the previous sections, reality-based interaction may be used to describe novel interaction techniques [73]. This model takes inspiration from the real world to describe interaction techniques. Specifically, the model encompass naïve physics, body awareness, environment awareness, and social awareness. Elmqvist et al. [40] suggested that reality-based interaction might provide fluid interactions for information visualizations. This, for example, promotes flow, support direct manipulation, and minimize the gulfs of action [106]. Proxemics interaction is related to the model of reality-based interaction [73] and have been explored in [9, 97].

In this short overview, I focus on contributions that have considered full-body interaction in the form of body translation, rotation, display distance, and display orientation. These interaction forms have particular relevance for large displays, because it is necessary to move in front of large displays to reach pertinent display areas. Many studies have investigated how people move in front of large displays and how people use the available display space. I cover this focus in the next section (section 2.2). With this scope, I exclude techniques that do not consider whole-body movement such as “mid-air” hand and foot interaction techniques (e.g., [31, 103, 132]), chair-based interaction techniques (e.g., [33, 43]), body-centric interaction techniques (e.g., [133]), and interaction techniques for virtual reality (e.g., [118]).

Using people’s distance to a display as an input has been subject to the most studies. In an early contribution, Vogel & Balakrishnan [154] described four interaction phases that spanned implicit to explicit interaction: ambient display, implicit interaction, subtle interaction, and personal interaction (see Figure 2.3). In addition to distance, the authors also discuss and use orientation towards the display. While the authors described these proximity-based interactions in terms of an information visualization, they only partly directed their interactions towards the visualization. Specifically, the authors note that participants moved laterally to adjust a detail time-line view. This form of interaction appeared easy to use for the study participants. Distance is also part of proxemics interaction [9, 97], where it is divided in social zones. Here, the definition is derived from the sociologist Hall’s work [58]. In particular, Hall divided distances between people in four zones: public, social, personal, and intimate zones.

Peck et al. [109] compared a novel interaction technique that mapped distance zones to target selection size on an large display to common interaction techniques. The authors asked study participants to solve a puzzle that involved swapping pieces at different hierarchical levels. The authors suggested that their novel interaction technique might have resulted in more natural behavior from participants in their study. When the participants used the novel interaction technique, they shifted less between the different hierarchies and seemed to use a more consistent strategy to solve the puzzle. The authors suggest this might indicate that the technique helped participants in obtaining and maintaining a better grasp of the task and data.

Lehmann et al. [93] described two interaction techniques for graph visualizations on large displays based on discrete distance zones. One technique (zone) changed the globally displayed graph hierarchy level. Far away, only high-level nodes were displayed. Moving closer showed more details. The other technique (lens) also provided details based on zones. This however, offered focus+context interaction, by only providing details for the area covered by the users’ gaze (approximated by head tracking). A preliminary user study suggested that although the lens technique felt more interactive and “eye-catching”, the zone technique was perhaps easier to use. The authors reported that participants experienced unintended interactions, which were caused by minor head motions, and suggested that adjusting the input filter might reduce these issues. In addition, they suggested to facilitate freezing the head tracking, for example to allow people to compare different nodes.

Rädle et al. [121] compared two zoom and pan techniques for a memorization task inspired by the childrens’ card game Memory. A tablet provided a zoom and pan interface for navigating a virtual scene. A large display showed the entire scene physically with the tablets’ area emphasized, thus providing overview (the two devices potentially providing overview+detail). Only the tablet showed the content of memory cards, and only when zoomed in fully. In one technique (multi-touch condition), participants were stationed in a chair and used a tablet for navigating a virtual scene of cards to memorize. In the other technique (egocentric condition), participants were free to walk around. Here, zoom and pan was dependent on the tablet distance and lateral position relative to the display. Interestingly, participants self-reported significantly higher mental workload for the stationary condition. Rädle et al. also reported that participants moved less in the virtual scene in the egocentric condition. This suggests that participants had a better overview of the cards' location in this condition. A limited experiment also showed long-term spatial memory benefits for the egocentric condition, and thus point to future work.

Dostal et al. [34] showed collaborative distance- and orientation-based interactions, with a focus on tracking people using a cheap off-the-shelf RGB and depth camera. Their contribution relies in coarse tracking of people to detect interaction zones and orientation for interaction purposes as described above.

Isenberg et al. [67] demonstrated a novel method of passively showing different information depending on display distance based on hybrid images. Even though the authors used a passive approach to vary visualizations based on distance, peoples' perception actually did change according to distance.

In this short overview, I described contributions that primarily considered peoples' distance and orientation to large displays. It is clear that these contributions have barely scratched the surface of the design possibilities. This description also concludes the overview of novel input and interaction technologies for information visualizations. Next, I describe information visualizations on large displays.

2.2 Information visualizations and large displays

There has been a tremendous proliferation in computing form factors. A decade ago, people primarily used laptops or desktop computing devices to access the Internet. Now, people spend more time online with their smart phone than any other device [104]. In contrast, large displays have recently emerged in research and commercially (e.g., [169]). In the following sections, I primarily include work focusing on large displays for information visualizations.

I distinguish between peoples' use of space to make sense of data (e.g., [3]), which is driven by peoples' spatial organisation, and using space to show large data visualizations with spatial encodings (which most visualizations rely on), which is driven by visualization algorithms. The following considers these two aspects separately.

2.2.1 Using space to make sense of data

People use physical space to make sense of data both individually and in groups. For example, they lay out pages of documents to gain an overview, stack piles of related documents to enable easy retrieval of vast amounts of such, or fix pertinent information on walls. The following considers these aspects.

Much of the early work on spatial management in HCI studied tabletop displays and focused on co-located collaboration. Such studies looked at orientation (e.g., [85, 86]), territoriality (e.g., [125, 124]) and different modes of collaboration (e.g., [69, 70, 141]). This work has identified implicit coordination mechanisms between collaborators and described how people divide work areas. Lately, larger displays and vertical displays have gained more attention. These displays have also been studied in collaborative contexts (e.g., [76]). Whereas these studies considered how people collaborate using space, other work has considered explicit support for collaboration with large or tabletop displays. Tobiasz et al. [143] integrated meta-visualizations in Lark to support coordination between collaborators. Hinrichs et al. [64] presented a user interface metaphor based on e.g., airport luggage carousels in interface currents. Isenberg & Fisher [68] presented Cambiera, which showed collaborators' searches through brushing and linking on a tabletop display. Isenberg et al. [69] subsequently evaluated Cambiera for sensemaking. Jakobsen & Hornbæk [76] adapted Cambiera to a large display and replicated the Cambiera study. Seifried et al. [128] suggested undo and redo techniques for large displays that used peoples' location as context for navigating the interaction history.

Other work have studied the use of whiteboards in both individual and collaborative contexts, without explicitly focusing on one or the other. These studies suggest that people use whiteboards for externalization of thoughts. Mynatt [101] reported how people used whiteboards to "get something out of [their] brain" and used it as a thinking device, in which the content of the board was only important after it had been drawn. She described how some people divided the space on whiteboards into storage and working spaces, in which people only removed content to make space for new content. Other people used a clean desk behaviour. Mynatt classified these as space scavenging and clean desk behaviours respectively. Similar findings were reported by Branham et al. [20]. Tang et al. [140] described people's use of whiteboards as persistent storage areas for information related to future tasks, to transition between different collaborative modes. They further described how the physical context influenced the manner in which people use whiteboards and what they draw on them. Walny et al. [156] studied people's use of visual representations on whiteboards to support thinking. The study showed people's varied use of representations and linking on whiteboards, and suggested that whiteboards affords an immediacy that large displays do not offer. In addition to providing insights on people's use of space, these studies showed the value in using whiteboards to inform designs of large display visualization and interaction techniques.

Whiteboards have also inspired a range of pen and touch interactions. Browne et al. [22] showed SketchInsight, which provided data exploration through free-form and sketchy interactions. Walny et al. [157] studied the use of a version of SketchInsight in a Wizard-of-Oz study setup, to learn the range of interactions that people would use naturally. Lee et al. [91] described SketchStory, which provided a medium for telling stories with data. Strokes on a large display was mapped to different visual representations of data, which could be prepared in advance.

Other contributions have focused on individuals' use of large displays for sensemaking. Andrews et al. [3] conducted a study in which participants used the "analyst's workstation", an 8-monitor 10,240x3200 pixels desktop display, to solve the VAST 2006 contest problem [56, 111]. They described study participants' externalization of memory and use of spatial organisation strategies. For example, they observed the use of sorting piles, mapping documents' date to a horizontal layout, and using lists and clusters. They described this as "space to think". From the insights of this study, Andrews & North [4] designed the "Analyst's Workspace". This was tailored to large desktop displays such as the "Analyst's Workstation". The tool supported document annotations and links between named entities (extracted and manually annotated). Singh et al. [135] presented a system that facilitated analysis of web logs on large displays. The system's visual representations focused on the state and transformations applied to data, to support people in keeping track of analysis hypotheses and conclusions.

While large displays seem to help people in making sense of data and provides space to think, some information visualization systems use virtual space, which is navigated with pan and zoom techniques (e.g., [37, 52, 80, 151]). Dunne et al. [37] used such an interface in GraphTrail, which showed links between visualizations that left a visual trail of data exploration. They observed that these links helped people to understand the actions that led to a visualization, recall the exploration history, and share analyses with others. Dunne et al. [37] reported that different analysts used different spatial arrangements, which carried meaning to them. However, understanding these arrangements required additional effort by their collaborators. In a parallel lab study, participants noted that the spatial organization of charts provided a useful overview, and aided in understanding related visualizations and branches in analysis.

The use of physical space compared to virtual space to make sense of data was studied systematically by Andrews & North [5]. They based the study on tasks and data similar to their previous sensemaking studies described above, and used a between-subjects study design. Participants used either a 17" 1280x1024 pixels display or eight 30" monitors at a combined display resolution of 10240x3200. Although the study did not show performance differences in the quality of findings (measured using the approach of Plaisant et al. [111]), it showed remarkable differences in how space was used across the two conditions. Most study participants assigned to the virtual condition did not organise the data spatially. One participant assigned to the virtual condition made an effort to organise data spatially. This participant made frequent mistakes. The authors argued that the need to access space virtually confounded him and impoverished his actual spatial sense. Further, that this might have been a deciding factor in this participant obtaining the lowest performance score. Most large display study participants organised data according to time, geography, or people, and created 75% more spatial structures. Additionally, these organisations were more complex. The participants categorised documents after reading them, spent more time referring back to previously read documents, and created more notes. However, the two groups of participants used different note-taking strategies. Where large display participants used notes to label documents and space, the small display participants used notes to synthesize their findings in narratives.

2.2.2 Using space to show large data visualizations

Visualization designers may use the space provided by large displays to show large visualizations. For example, the additional space afforded by large displays may be used to partition visualizations using composite visualization techniques [79]. North and colleagues studied this area in several experiments. Yost et al. [166] explored the degree to which visualizations can be scaled while maintaining user performance. Specifically, they compared a display-wide geographically based layout (space-centric) to a layout based on an attribute table (attribute-centric). In a follow-up experiment, Yost et al. [165] explored the effects of scaling visualizations to the point of, and beyond, visual acuity. Results of the experiments suggested that large displays increase people's efficiency and accuracy and that the geographically based layout, particularly on large displays, was superior for many tasks. Shupp et al. [134] studied the role of display space and curvature with a range of tasks on geospatial and demographic data. They found improved performance with large and in particular large curved displays, which is likely to stem from the fact that people could move between displays by rotating, rather than translating movements. Additionally, they suggested that because the display was flat, participants could step back from the display and visually aggregate the data. This influenced participants' initial insights, which were more at the overview level, for example evidenced by their observations of global trends and patterns.

Jakobsen & Hornbæk [75, 74] studied the role of display space and information space in two experiments with similar tasks as North and colleagues. The experiments compared three interactive visualization techniques for multi-scale navigation: focus plus context, overview plus detail, and zoom and pan, across three display sizes, and information spaces fixed or relative to the display sizes. In contrast to other work, their controlled experiments showed no significant performance benefits from large displays. They noted that their choice of tasks influenced the results, for example, by targets being visible irrespective of zoom level, by requiring interaction with display targets, and by not requiring wide use of information at multiple levels of scale to solve tasks. Liu et al. [95] compared classification tasks using pan-and-zoom interaction on a desktop-size display to physical navigation in front of a large display. Their results suggested that desktop-size displays are faster than large displays for simple tasks, while large displays benefits more difficult tasks. Reda et al. [112] studied visual exploration tasks for two large displays sizes. Their results suggested that people generate more hypotheses and observations with larger displays. Ruddle et al. [117] studied visual search across three display sizes ranging from 20 to 129 inches. While the largest display showed the entire information space, the smaller displays required participants to pan. Their results suggest benefits from large displays to show entire information spaces, but note that many tasks that do not fit this limitation.

2.2.3 Using space as part of regular office work

Some studies have identified benefits to using large displays for office work (e.g., [17, 30]). While such work is interesting, the findings and implications from it is of limited interest in considering large display work for specific applications of information visualization.

2.2.4 Large displays and physical movement

Several studies have considered how people move and navigate physically in front of large displays (e.g., [8, 9, 16, 42, 67]). Ball et al. [8] showed performance improvements of physical navigation over virtual navigation in front of a large display, and attributed the benefits to the directness of the physical navigation. Their work is supported by Liu et al. [95]. While these studies suggest that physical movement in front of large displays can be beneficial, the exact reasons remain unclear. Further increasing the complexity, Jakobsen & Hornbæk [77] showed no benefits of physical navigation when they experimentally controlled participants' movement.

Other studies have considered people's position in front of large displays. For example, Endert et al. [42] and Bezerianos & Isenberg [16] studied peoples' perception of visual encodings in front of large displays.

2.2.5 Summary

In the previous subsections, I have described contributions that studied information visualizations on large displays. First, people can use the space provided by large displays to organise and navigate large data sets. Studies have suggested this improves peoples' ability to manage information and supports thinking [3]. Secondly, visualization designers can use the space provided by large displays to show large visualizations with spatial subdivision (e.g., based on composite visualization techniques [79]). Additionally, large displays enable people to use physical navigation which might be beneficial [8].

These contributions have shown benefits of using large displays for a range of applications. In the next section, I outline questions relating to interaction with information visualizations on large displays, which related work have not addressed.

2.3 What is it that we still do not know?

In the previous sections, I have outlined work that studied novel input technologies (e.g., [107]), interaction techniques (e.g., [10, 154]), and large displays (e.g., [8]) for working with information visualizations.

From this overview, it is clear that there are many open questions and possibilities for combinations of these. Much research on large displays have dealt with how users can interact with large displays, and proposed and evaluated interaction techniques (e.g., [68, 143, 157]). Less work has considered support for complex data analysis. Some studies have helped to advance our understanding of how single (e.g., [3]) or multiple users (e.g., [19, 76]) benefit from large displays in data analysis tasks. However, they have rarely identified new visualization or interaction techniques for using space to think.

Although recent studies have helped to understand complex data analysis tasks with large displays, we know little about how to support data analysis beyond efficient pointing and window manipulation techniques. It is unclear how abundant display space can support data analysis tasks in general. Moreover, we lack visualization and interaction techniques that help users benefit from large displays when analysing large amounts of data.

This raises several questions. For example:

- How might abundant display space support exploration of large data sets?
- How might abundant display space be used to reason about alternatives?
- Can we design interaction techniques for abundant display space that support analysts in data exploration and hypotheses testing?
- How might we tailor interaction techniques to abundant display space, and thus leverage the affordances they provide?

The next part of this thesis describes the four papers that comprise my thesis work. I devote a chapter for each paper. The papers aimed, in different ways, to answer the questions outlined above. After describing the four papers in Part II, I end the thesis in Part III, which comprise Chapter 8 and 9. In Chapter 8, I discuss the methodology and findings of my thesis, before concluding the thesis in Chapter 9.

Part II
Contributions

Chapter 3
Overview of contributions

My thesis work and contributions concern information visualizations on large displays driven by novel interaction techniques. In the following chapters that comprise Part II of the thesis, I describe my contributions to the HCI and InfoVis fields based on four papers.

The central research question has been:

> *How may abundant display space support visualization-based data analysis?*

In my contributions, this question has been approached from different positions. I have devoted a chapter to present each paper individually and to outline how it contributes to answer the central research question. Figure 3.1 shows how the studies described in the next chapters were inspired by the previous studies. I leave discussions and conclusions of the individual contributions to the final chapters of the thesis in Part III.

In Chapter 4, I describe a study with many groups of domain experts. In the study, we ask the domain experts to imagine working with their tasks and data on a large display, simulated by a whiteboard. From a synthesis of observations from the workshops, the study identifies six dimensions to consider in designing analysis tools for large displays: *persistency*, *transience*, *juxtaposing*, *trail of thoughts*, *movement*, and *gestures*. These dimensions work as inspiration for the following chapters of the thesis, and thus suggests potential ways in which abundant display might support visualization-based data analysis.

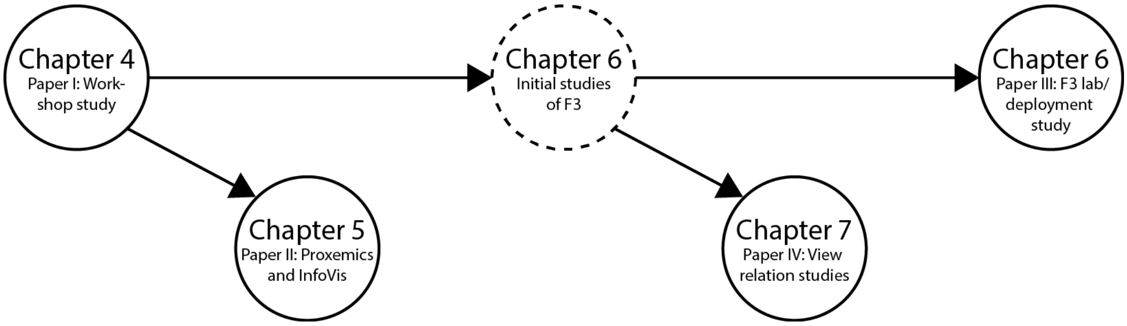


Figure 3.1: Overview of individual contributions.

In Chapter 5, I describe three formative studies of the *movement* dimension. This dimension (unsurprisingly) relates to movement in front of large displays, and thus concerns analysis with abundant display space. The studies described in this chapter explore the dimension in more depth by developing designs that map the InfoVis task and proxemics interaction frameworks. With abundant display space, it is necessary to provide techniques that, for example, allow visualizations to follow people where they move. Thus, proxemics are relevant to consider in relation to abundant display space. I conclude the chapter with findings from the studies synthesised across the three studies.

In Chapter 6, I describe a specific domain of analysis and contribute interaction techniques for working with large multidimensional data sets on large displays in this domain. The work is based primarily on the *transience* and *trail of thoughts* dimensions, both of which I describe in Chapter 4. The interaction techniques are implemented in a system, F3. I conclude the chapter with descriptions and findings from empirical studies of F3, which we deploy within the specific domain of analysis in one of the studies. Chapter 6 thus works to show specific ways in which visualization-based data analysis might be performed with abundant display space, by designing and evaluating specific interaction techniques for working with multiple views and abundant display space.

In Chapter 7, I describe a lab study on view relations with visualization and interaction design experts. This work is based primarily on how participants in the study described in Chapter 4 had shown visualizations' relations with *trails of thoughts* and the process of designing F3, which is described in Chapter 6. Specifically, I observed participants confusion in a small informal lab study of an initial version of F3, that did not show relations. In the study, which I describe in Chapter 7, we ask the participants to work with, discuss and sketch representations of view relations. Our results, together with existing research, form the basis of a six dimensional framework that expands the range of possibilities of view relation representations. By contributing this framework, Chapter 7 thus shows the wealth of techniques that might be used with many views and abundant display space. In this manner, the chapter thereby suggests the many alternative ways that visualizations might be used with abundant display space.

In the following, I use the term *"we"* to refer to work that was conducted collaboratively as part of studies. Likewise, I use the term *"I"* to provide descriptions of work prior to any collaborations, to provide additional explanations compared to submitted research papers, and when providing meta-language to guide the reader in reading the text.

Chapter 4

Paper I
An Exploratory Study of How Abundant Display Space May Support Data Analysis

S. Knudsen, M. R. Jakobsen & K. Hornbæk

Abstract – Large, high-resolution displays offer new opportunities for visualizing and interacting with data. However, interaction techniques for such displays mostly support window manipulation and pointing, ignoring many activities involved in data analysis. We report on 11 workshops with data analysts from various fields, including artistic photography, phone log analysis, astrophysics, and health care policy. Analysts were asked to walk through recent tasks using actual data on a large whiteboard, imagining it to be a large display. From the resulting comments and a video analysis of behaviour in the workshops, we generate ideas for new interaction techniques for large displays. These ideas include supporting sequences of visualizations with backtracking and fluid exploration of alternatives; using distance to the display to change visualizations; and fixing variables and data sets on the display or relative to the user.

My contributions to Paper I

I devised the study design supervised by last author and my supervisor, Professor Kasper Hornbæk.

I carried the main responsibility of collecting data through recruiting participants, interviewing participants, organising the workshops, and analysing the collected data. These are all described in this chapter.

I wrote all parts of the manuscript except for related work and discussion, which I contributed revisions to.

In the first paper of the four papers that comprise my thesis work, we sought to explore the research question by inquiring into many data analysis disciplines. Doing so, we wanted to find specificities in individual disciplines that were generalizable across disciplines, in a concrete, real-world manner. We approached the problem in a naïve and technology-less way, where we asked analysts that participated in workshops to imagine doing their analysis tasks, given abundant display space. In reality, they were using a whiteboard. The approach was naïve in that no framing of the problem had been defined, except for a wish to understand the implications of abundant display space for data analysis. This with the intent of walking into the problem with a so-called clean slate [139]. Similarly, the approach used no modern technologies during the workshops, for arguments similar to lo-fi prototyping (e.g., [113, 116, 136]). However, workshop participants used the technology they were comfortable with to prepare tasks and data in printed form. Participants brought these tasks and data to the workshops to keep it grounded in concrete work.

4.1 Methodology

We conducted eleven workshops with small groups of 2 to 3 data analysts from diverse fields, including artistic photography, phone log analysis, astrophysics, and public health care analysis. Data analysts were taken to mean people that perform tasks that has been classified as data analysis tasks [100] as a regular part of their work. The top of Table 4.1 provides an overview of the study and the applied methods. I repeat this table structure across the studies described in this thesis. The bottom of Table 4.1 shows the individual workshops.

We designed the study to learn about diverse ways of conducting data analysis in a broad range of domains, and thus comprising a broad range of data, tasks, and methodologies. We chose to conduct a workshop study because we wanted to observe real, hands-on analysis work, carried out on what participants would think of as a large interactive display. The key part of the workshop was to make participants imagine a whiteboard to be a large display and then redo their own tasks on the imaginary display. This approach offered several benefits. First, the approach was more general than individual studies of data analysis. Second, the approach was grounded in concrete data analysis tasks, rather than trying to develop general models of analysis activity and derive design implications from them. Third, the approach offered a sweet spot between contextual studies and generalizability. Fourth, while many methods rely on being present in-situ while work is being conducted, the workshops allowed participants to imagine working with tasks that spanned extended periods of time.

In the workshops, the analysts worked with tasks and data that they brought to the workshop in printed form. A 6 by 1.3 meters whiteboard mimicked a large display. Workshops lasted approximately 2 hours and most covered two tasks. We began working with a task by asking participants to fix the printed data to the whiteboard using magnets as a starting point for imagining working with the concrete tasks. Then, a member of the group explained the task. After the explanation, the group were encouraged to discuss the task more freely and to imagine to solve it using abundant display

Paper	Aim	Method	Collected data	Analysis	Medium	Participants
I	Elicit tasks	Interviews	23 task descriptions & 452 sheets of data printed on A4 paper sheets	Ad hoc	-	Domain experts
I	Explore large displays Info-Vis in many domains	Workshops	17 hours of video	Grounded Theory	Whiteboards and printed sheets of data	Domain experts

Work-shop	Participant characteristics			Materials used in the workshops	
	#	Domain	Type and magnitude of analysis data	Tasks	Representations of data
A	■■■	P Health care policy	Operations data on 1 mil. annual admissions to Danish hospitals.	Understand errors in computing costs of hip replacement surgery based on activity information from hospitals.	3 sheets of tabular data and 3 sheets of histograms covering a subgroup of replacement surgery (hips).
B	■■	B Website analysis	Logs of 2.000.000 annual visits to an international corporate website.	Understand how use of the website relates to country of visitor and means of access (mobile or laptop and desktop).	89 printouts of reports from Google Analytics based on website in question.
C	■■■	P Health care policy	Financial and operations data on 1 mil. annual admissions to Danish hospitals.	Compute costs of births with and without epidural block and understand how changes in configuration of financial accounts influence diagnose group costs.	2 sheets of aggregated costs of patients, grouped by disease category; 14 births split on hospitals and 28 sheets with financial accounts of a specific hospital.
D	■■	B Use log analysis	Logs of 5.000 users' smart-phone activity.	Understand how separate subscriber segments use smartphones during a day.	Sketched individual and aggregate data over time for particular segments.
E	■■	R Astro-physics	Raw and processed images of 1.000.000 galaxies.	Understand relation between image features and properties of galaxies.	Raw and processed images of galaxies in 3 different sizes.
F	■■■	B Logistics	Positioning information of 10.000 containers on shipping vessels.	Stow containers into partially loaded vessel at current port minding stability, stresses of vessel and optimal ballast use.	14 sheets of user interface from an actual product used for analyzing loads of containers on shipping vessels.
G	■■	R Game statistics	Logs of 1.000.000 internet game users in-game activity.	How are communicational patterns defined and how does this relate to player age, leveling and number of players?	20 sheets of: a tabular overview of database tables, a box and whisker, 2 scatter, and 3 bar plots.
H	■■	R Information retrieval	Mappings of 30.000 rare diseases to 120.000 medical concepts.	Understand relation between mappings; why these results and why poor/no match.	20 sheets of tabular data describing input to and output from a semantic mapping tool.
I	■■■	R Information retrieval	Results of 1k queries to an information retrieval system based on 1M documents.	Gain overview of different information retrieval scores and their relation considering the queries.	3 sheets of tabular data describing query results towards a search engine covering rare diseases and aggregates based on 27 information retrieval metrics.
J	■■	A Artistic photography	100.000 photographs of people in the street.	Sort photographs in categories, construct new categories and select photographs to use in an exhibition and design physical arrangements for these.	100 photograph sheets covering 5 different categories. All photos from each category were printed on contact sheets as well.
K	■■	P air emission statistics	Statistical reports from multiple public sources.	Find and extract relevant information and analyze sources to understand trends.	8 sheets of paper with data describing air pollution in the EU.

P: Public organisation
B: Private organisation
R: Research body
A: Arts

Table 4.1. Overview of study methods, characteristics of participants' domains and data analysis tasks.

space. We probed the workshop participants with questions inspired by; (1) information visualization taxonomies [25, 129, 164]; (2) the possibilities enabled by large displays and how participants would use them; and (3) the tasks brought to the workshop.

The eleven workshops were video recorded. These videos contributed the main part of data collection, and were analysed using a grounded theory approach [139], which resulted in the themes described next.

4.2 Results, Findings, and implications

In the following, I give an overview of six themes. Paper I described some of these themes with a different name. I italicise this name in the text. These were the result of analysing the study data. The themes relate to various aspects of abundant display space. When describing how participants imagined the whiteboard as a display, I simply describe it as a display.

4.2.1 Persistency

Persistency related to setting aside space for one purpose and thus keeping some information visible in a fixed position for an indefinite time. One might for example imagine an overview visualization or a table of raw data displayed in a specific spot throughout an analysis session, a day, a week, or perhaps an entire project.

In workshop F, participants considered methods for allocating containers on shipping vessels. They imagined displaying a persistent overview of the load of an entire vessel, while they imagined smaller menus to follow the user while interacting. In workshop J, where participants considered analysis of photographs, they imagined using the left part of the display to show thumbnails of photographs throughout an analysis session. In workshop D, participants considered analysis of cell phone subscribers' use of smartphones. A participant reserved the top part of the display for simple data representations (e.g., histograms) of variables preselected among all variables in the system (for example gender, age, and smartphone model). These representations could be used to modify data representations in a working area in the central region of the display.

In contrast to persistent use of space, many participants imagined working areas, which users would modify while working with data. This is similar to other studies' (e.g., [124]) description of space division on tabletops. Working areas were kept in persistent locations. This was clear in several workshops. In other workshops, while the working area was persistent, this idea was not considered by participants.

The concept of persistency is relevant to the principal research question. With abundant display space, participants imagined that setting aside space for a single purpose for an extended amount of time, would make sense and be useful. This extends the notion of storage space as defined in related work. This finding also fits squarely with Mynatt's report of whiteboard use [101] (i.e., some whiteboard users had a known hot spot, where material changed frequently, which was bordered by more persistent content).

4.2.2 Transience

Transience related to temporarily using *space to spread out data*. For example, to use abundant space to show large menus with rich visualization temporarily. This might facilitate navigation of large information spaces by way of transient menus that show detailed information for each item in the menu. For example, to filter a visualization, that visualization might be displayed in different value groups of a data variable, similar to the small multiples visualization technique [147]. From this menu, users might select the specific filter group. This can potentially result in many visualizations to choose from, which may temporarily take up a large display area.

In workshop J, participants worked with artistic photography. They imagined transiently spreading photography tags across six meters of the display, to tag photos, after which the display would collapse the spread. The tags would be shown by one or more previously assigned representative photographs. In another workshop, participants imagined using transient overviews as an entry point to data. They imagined temporarily seeing an overview table with results of many simulations from an information retrieval study, and then go into detail, instead of having to go through the results one by one.

This use of space is in contrast to the previous theme, in terms of both the duration of time that abundant space is used, and in the application of the abundant space. The use of space is transient and may be applied to quickly select or modify data in short-lived visual representations of data, before moving on to something else.

The concept of transience is relevant to the principal research question. With abundant display space, participants imagined that using large amounts of space for very transient things such as menus, would enable them to quickly get to what they needed, with rich visual representations supporting their goal at hand. This is in contrast for example to menus that in many systems are primarily text based and takes up a relatively small part of a display.

4.2.3 Juxtaposing

Juxtaposing or in Paper I, *showing data side-by-side or one-by-one,* related to showing visualizations across time or space. Participants considered seeing versions of visualizations next to each other or alternatively seeing a single visualization transitioning from one version to the other. For example, seeing two bar charts next to each other that encode the same variables for different data can facilitate comparison. Incidentally, transitioning back and forth between the same bar charts, might also facilitate comparison.

For example, in workshop E, participants considered how to compare visual properties of images of two galaxies. They compared grayscale images, processed images, and image feature-plots of the galaxies spatially by aligning the galaxy images one above the other. In workshop I, participants imagined comparing sets of data by transitioning back and forth between them to view page ranks for different information retrieval algorithms, which they preferred over viewing data sets next to each other. They argued this would allow them to see how different pages moved from one algorithm to the other.

These contrasting ways of seeing versions of a data set was considered mainly in two ways: (1) to compare different version of a data set (as described above), and (2) to drill down in data by filtering on variables and segregating data. I describe this next.

In workshop C, where participants considered how to analyze cost structures in Danish hospitals, they used a stacked bar chart of costs of related diagnoses at individual hospitals. The participants imagined that selecting a bar would open another visualization next to the stacked bar chart, that would show more details for the selected bar. In this style, more detailed representations of data was shown next to a sort of overview, thus using space multiplexing. In workshop D, participants considered analysis of smartphone usage logs. They imagined the display to show a centered working area that would show a line chart of smartphone usage over a 24-hour period. They imagined to drag variables onto this data plot and thereby let the variables act as filters for the data shown. In this style, more filtered representations of data was obtained in the same area as the original view, thus using time multiplexing. This use of space primarily considered the use of a working area. It should be noted that the two alternatives are not mutually exclusive. In fact, interactive systems should probably support both working styles in a fluent manner.

Considering visualization juxtaposition is relevant to the principal research question. It is questionable whether space should always be used in comparing data sets given abundant display space. For example, comparing a bar chart filtered with a binary dimension might give much better impression of the relative differences between the two values. Likewise, seeing transitions in a time-varying scatterplot by interacting with a time slider helps users to follow the movement of individual points. In contrast, using small multiples to convey the same information would require the use of another visual variable (e.g., colour) to identify data points across visualizations.

4.2.4 Trail of thoughts

Trail of thoughts related to using abundant display space to show analysis provenance. The theme concerned capturing the history of data analyses by keeping records of interaction. Systems might use these records to represent the analysis provenance with visualizations. Participants considered the value of being able to see earlier steps of analysis by having these steps represented visually; participants also referred back to and used representations of such steps in the workshops. In some workshops, visualizations were connected using lines, thus providing a meta-visualization that represented flow of data. In other workshops, snapshots of the display state were shown in miniature version in a horizontal line at the bottom of the display.

In workshop G, participants were concerned with analysis of internet game statistics. They drew steps of data processing as vertices and the order of processing as edges. The participants explained that it was useful to have an overview of how data were processed and to be able to return to earlier analysis steps. Results from individual vertices could be represented using histograms or other representations. We had a related observation in workshop C, where the participants were concerned with analysis of health care cost distributions (also described in previous section). Here the steps were represented directly by visual representations of results instead of by vertices. Participants imagined that selecting a data point in a visualization would show a visualization with details about the data point. The data point would additionally be connected to the detail visualization using a line. Participants further imagined that this process could continue deeper into the data, thus revealing a “trail of thoughts”. In workshop G, participants discussed how to annotate important findings while analysing data, to be able to summarize insights at the end of an analysis session. They imagined a space-time capture of the analysis progress displayed in a horizontal line at the bottom of the display. Nearing the end of an analysis session, they imagined how they would go through the analysis to summarize their insights and open questions.

This use of space is different from the previous themes. The previous themes primarily related to the reduced necessity of space management. In contrast, this theme suggests novel approaches for using abundant display space, which may lead to new possibilities. In addition, where the other themes appear to be quite simple and uncomplicated, it appears as if the workshop study only scratched the surface of how to provide analysis provenance and meta-visualizations.

Considering how space may be used to provide a provenance trail is relevant to the principal research question. Thus, in contrast to the other themes that seem relatively well understood, this theme opens up more questions than it answers.

4.2.5 Movement

Movement related to people's movement in front of and distance to the display. The size of the display seemed to cause participants to move around in front of the display, and moving back and forth in front of it. Moving away from the display seemed to allow participants to obtain an overview. Moving closer seemed to facilitate seeing details. When participants moved in front of the display, they did so to get closer to data or views of interest, to move out of other participants' view, to gather an overview, or to point to something on the display.

Participants moved to and from the display in most workshops. In a workshop J in which participants imagined how to lay out photos for an artistic photography exhibition, participants moved close to the display to look at details in specific photographs and quickly back again to position this detail in their overview. A participant said: "I can construct an overview of the photographs; I can see what's on the photographs while still being able look at the entire overview". In this workshop, it was important to present data (i.e., photographs) to outsiders. The sequence of first standing away from the display and thinking, then walking up close to interact with the display and then slowly backing up, as if to make sure things were as expected, was seen in all but three workshops. It was however, most visible in the photography workshop, where three positions in relation to the display were observed: Interacting or looking at the display (close); with the back turned to the display and interacting with other participants (middle); and away from the display facing it (far). Sorting the grabbed images into these categories showed that participants in this workshop spent an equal amount of time in all three positions.

Some participants took micro steps when working in front of the display. In workshop E, where participants imagined conducting analyses of galaxy images, a participant stepped half a step backwards to get distance from the display and to get an overview. Another variant of movement relates to small movements with both feet on the ground. We observed this in a workshop B where participants considered how to analyse website statistics. A participant that worked on a task in one area of the display needed to look at data placed in another area. To be able to see data located far away at the display, he leaned backwards, thus getting an improved field of view to the distant display area, while holding onto the data in front of him.

The ways that participants moved relates to using abundant display space, but in a different manner compared to the previous themes. When there is a lot of space, it might be necessary to look at data located far away. Likewise, moving away from the display helps to overview data, similarly to virtual navigation. It is possible to use both of these types of movement to direct implicit interaction. For example, micro steps might initiate a zoom mode that scales up the gaze area. Likewise, walking away from a display might enhance the physical navigation with virtual scaling.

4.2.6 Gestures

Gestures related to the types of gestural interactions that participants imagined or performed on or in front of the display, which related to abundant display space. Thus, we did not code gestures that participants used to communicate with other people, due to the frequency in the study and our focus of the analysis. The behaviour that we analysed was for example when participants dragged things on the display, waved their hands in front of the display, or talked about interacting with the display by pointing.

We observed 172 gestures that matched the described behaviour. These gestures were grouped in three categories according to their type: (a) on-screen (9 workshops, 44 gestures); (b) in front of screen (8 workshops, 43 gestures); and (c) in-air gestures (10 workshops, 85 gestures). Previous work have described most of these gestures. For example, we coded 46 instances of sync- or asynchronous bimanual interactions. A group of behaviour that surprised us was the use of very large gestures. We saw 13 large gestures across six different workshops, and considered the size of the gestures to relate to display space. In a workshop J where participants considered how to arrange photographs for an arts exhibition, the participants talked about changing overall states of the display. In this context, a participant imagined dragging an image view that spanned the height of the displaying from one end of the display to the other (six meters) to re-arrange the layout. Later in the workshop, another participant imagined to use a gesture to move a view to his current position in front of the display.

The observation of interaction techniques that spanned several meters surprised us and seemed interesting to pursue. We imagined that most people would feel awkward performing what looks more like dance movements than “serious work”. The existence of what I have described as large gestures indicates that a dimension of gestures relate to their size. Additionally, there might be a relation between display size and gesture size. If such a relation exists, then large gestures for small devices might not be useful. Vice versa, small gestures for large displays might not be useful.

Thus with abundant display space, the size of gestures may also be very large, and potentially require collaboration between people.

4.3 Summary and conclusion

In this chapter, I described six themes that occurred across a varied range of data analysis domains. The themes inspired the papers that I describe in the next chapters. The themes' inspiration for the papers was:

- Persistency
- Transience / *space to spread out data* (Paper III)
- Juxtaposing / *showing data side-by-side or one-by-one* (Paper III and IV)
- Trail of thoughts (Paper III and IV)
- Movement (Paper II)
- Gestures (Paper III)

Chapter 5

Paper II
Information Visualization and Proxemics: Design Opportunities and Empirical Findings

M. R. Jakobsen, Y. S. Haile, S. Knudsen & K. Hornbæk

Abstract – People typically interact with information visualizations using a mouse. Their physical movement, orientation, and distance to visualizations are rarely used as input. We explore how to use such spatial relations among people and visualizations (i.e., proxemics) to drive interaction with visualizations, focusing here on the spatial relations between a single user and visualizations on a large display. We implement interaction techniques that zoom and pan, query and relate, and adapt visualizations based on tracking of users' position in relation to a large high-resolution display. Alternative prototypes are tested in three user studies and compared with baseline conditions that use a mouse. Our aim is to gain empirical data on the usefulness of a range of design possibilities and to generate more ideas. Among other things, the results show promise for changing zoom level or visual representation with the user's physical distance to a large display. We discuss possible benefits and potential issues to avoid when designing information visualizations that use proxemics.

My contributions to Paper II

I took part in identifying the possibilities within the design space of information visualizations and proxemics, and was the main force in developing design #3 described in this chapter. This included UI design, software development, and evaluation.

I took part in the evaluation of all three designs and in the subsequent analysis of these designs, which are described as study #1 to #3 in this chapter.

I wrote the first draft of the section describing study #3. In addition, I contributed revisions to other sections of the paper. Additionally, I was solely responsible for creating the video that formed part of the submission.

In the second paper, related HCI literature and participants' movement in the first study inspired us, to understand how users' distance and orientation to large displays might be used to interact with information visualizations. We wanted to understand the possibilities of considering body movement as explicit interactions with visualizations. Our aim was to generate design ideas, and to obtain initial data on the usefulness of combining movement with information visualizations.

To do this, we explored the possible combinations of distance and orientation on one side, and peoples' need to perform low-level visualization tasks on the other side. We identified proxemics interaction [97] as a starting point for exploring the design space of combining primarily the distance and orientation dimensions from this framework with information visualizations. Likewise, to structure our support for interaction with information visualizations, we chose to base our further work on Heer & Shneiderman's taxonomy of visualization tasks [61].

We gave a thorough description of the design space covered by the combinations of these frameworks (i.e., [61, 97]) and described related work in terms of this design space.

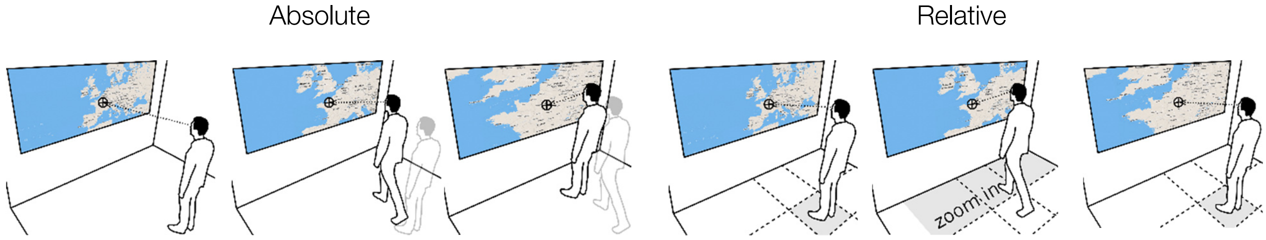
We implemented three variations over these possibilities, and evaluated each variation in a formative lab study with six participants in sessions of approximately an hour per participant. The lab studies were based on two to three conditions that compared the novel interaction techniques to mouse-based interaction techniques. We interviewed participants to learn about their experiences and thoughts about the novel interaction techniques. After conducting the six sessions, we analysed the interview notes based on the instant data analysis technique [84]. We compiled the results of these analyses, which then formed the basis of the paper's empirical data. Table 5.1 provides an overview of the methods used in the studies.

5.1 Designs

The three designs focused on distance and orientation of a single user interacting with a single visualization on a large display. In the evaluation, we compared all three designs to a baseline interface condition using mouse input. I will not describe the mouse interface in detail, since it was primarily included as a comparative condition in the evaluation. We chose this approach, because previous work has suggested that participants generate more comments, when they are able to compare alternatives [144]. I give a brief description of each design in the following.

Paper	Aim	Method	Collected data	Analysis	Medium	Participants
II	Evaluate design #1	Formative evaluation	Observation notes & memory	Instant Data Analysis	Large display and body tracking	No specific background
II	Evaluate design #2	Formative evaluation	Observation notes & memory	Instant Data Analysis	Large display and body tracking	No specific background
II	Evaluate design #3	Formative evaluation	Observation notes & memory	Instant Data Analysis	Large display and body tracking	No specific background

Table 5.1: Overview of study methods.



(a) (b) (c) (d) (e) (f)

Figure 5.1: Zooming in the two interfaces that use proxemics in Design #1. In Absolute (a-c), the zoom level increases as long as the user keeps moving toward the display, and stops zooming when the user stands still. In Relative (d-f), the zoom level increases at a constant rate, as long as the user is within the zoom zone (e). Zooming is centered on a crosshair, which indicates the point where the ray cast from the user's head intersects the display.

5.1.1 Design #1

The first design used a zoom+pan interface for navigating geographical maps. We designed two interfaces based on proxemics interaction.

The first movement based interface (absolute) used a direct mapping between physical movement and movement of the map. Moving toward the display zoomed in and moving away from the display zoomed out; see Figure 5.1 (a to c). Zooming was centred based on head orientation, which we indicated by a crosshair shown on the display. Lateral movement controlled horizontal panning: Moving left caused the map to move right; moving right caused the map to move left. We used head orientation for panning up and down by pitching the cap such that the crosshair would approach the top or bottom of the display. Panning in both dimensions happened at a fixed rate.

In the second movement based interface (relative), moving relative to a 75cm by 75cm rectangular region in the centre of the floor controlled zoom and pan; see Figure 5.1 (d to f). Being physically left of the region caused the map to move right; and being physically right of the region caused the map to move left. Similarly, stepping toward the display from the region caused the map to zoom in; and stepping backward from the region caused the map to zoom out. The zoom rate was inversely proportional to the zoom level such that when zoomed in to a detailed level, the zoom rate was lower. Moving further away from the region did not affect zoom rate. The use of head orientation for zooming and for vertical panning was similar to Absolute.

5.1.2 Design #2

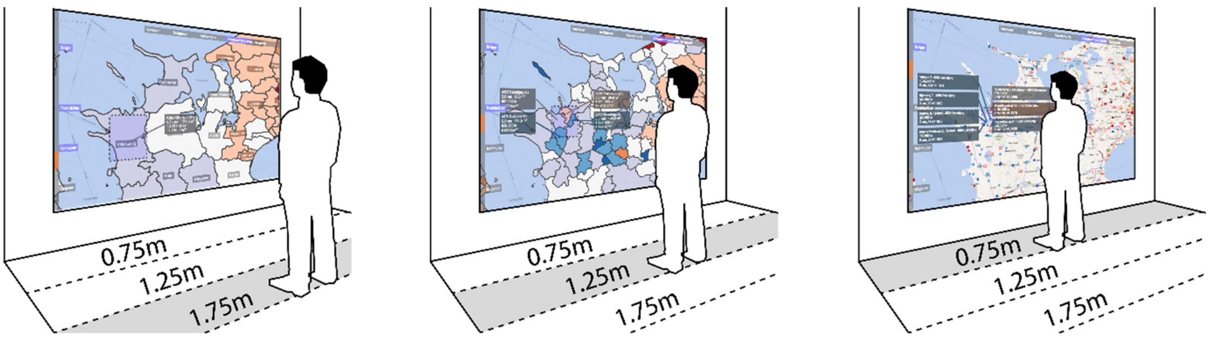
The second design adapted a visualization using semantic zoom of a colour-encoded map based on physical distance and orientation. We designed one interface based on proxemics interaction.

The distance- and orientation-based interface varied the level of visual aggregation of data attributes based on distance and provided details based on head orientation. First, we used a diverging colour scale to indicate to which degree the value of an areas' attribute was above or below the mean value for that attribute. At less than 75cm from the display, individual homes were shown as points. With increased distance, the representation changed to show data aggregated on geographic areas (75cm: Danish postal districts; 125cm: Danish municipalities, 98 municipalities in total; 175cm: Danish regions, 5 regions in total), and used larger font sizes. Transitions between representations used alpha blending over a 20cm distance range. Second, we used movement-based Excentric Labelling [45] to give details about homes within a selection box that followed physical position horizontally and moved vertically with the pitch of the user's head. Third, we used multi-scale interaction [109] to control the size of the selection box. It grew in size with increasing distance and showed details for data at higher scales: homes, districts, or municipalities. Fourth, we used movement-based change of colour encoding. When more than 250cm from the display, the attribute menu (which was shown in the top-centre area of the display) responded to lateral movement: Moving left or right caused an indicator to move to another attribute that would be used for colour encoding.

5.1.3 Design #3

The last study investigated the use of distance for selecting attributes, filtering, and brushing and linking multivariate data. We designed one interface based on proxemics interaction.

The distance-based interface displayed data in multiple coordinated views. The interface comprised a window that contained nine scatterplots and a data table, a view that showed a histogram for a single attribute, and a view that allowed for selection between nine attributes in a list. When selecting an attribute from the list, the histogram for that attribute was shown and the data table was sorted by



(a) Aggregate, municipalities (b) Aggregate, postal districts (c) Individual homes

Figure 5.2: Techniques used in Design #2. (a) and (b) Distance-dependent aggregation of real-estate data by geographic area; and details on demand for geographic areas. (c) shows real-estate data for individual homes with data points; and details on demand for individual homes.

that attribute. For visualizing the histogram, the values of most attributes were binned to produce 10 bars. For attributes with less than 30 values, each value had its own bar. Users could select histogram bars. This would filter the table view to show only the corresponding data points and mark corresponding data points in the scatterplots red.

The attributes in the list mapped to discrete distance zones from the display; 100cm (the first attribute) to 250cm (the last attribute) from the display. An attribute was selected by moving closer or farther from the display, shown in Figure 5.3 (b to c). In the attribute list, a circle indicated the physical position relative to the attribute zones. Hysteresis tolerance was used for transitions between the zones of two variables: Entering and exiting a zone was facilitated at separate distances, with the intention to avoid unintentional switching back and forth between two attributes. Sideways movement caused brushing over bars in the histogram: Lateral position relative to the display mapped to the x-axis of the histogram; see Figure 5.3 (a to b). One bar was selected at a time. The physical space for brushing (from the leftmost to the rightmost bar) spanned 165cm centred relative

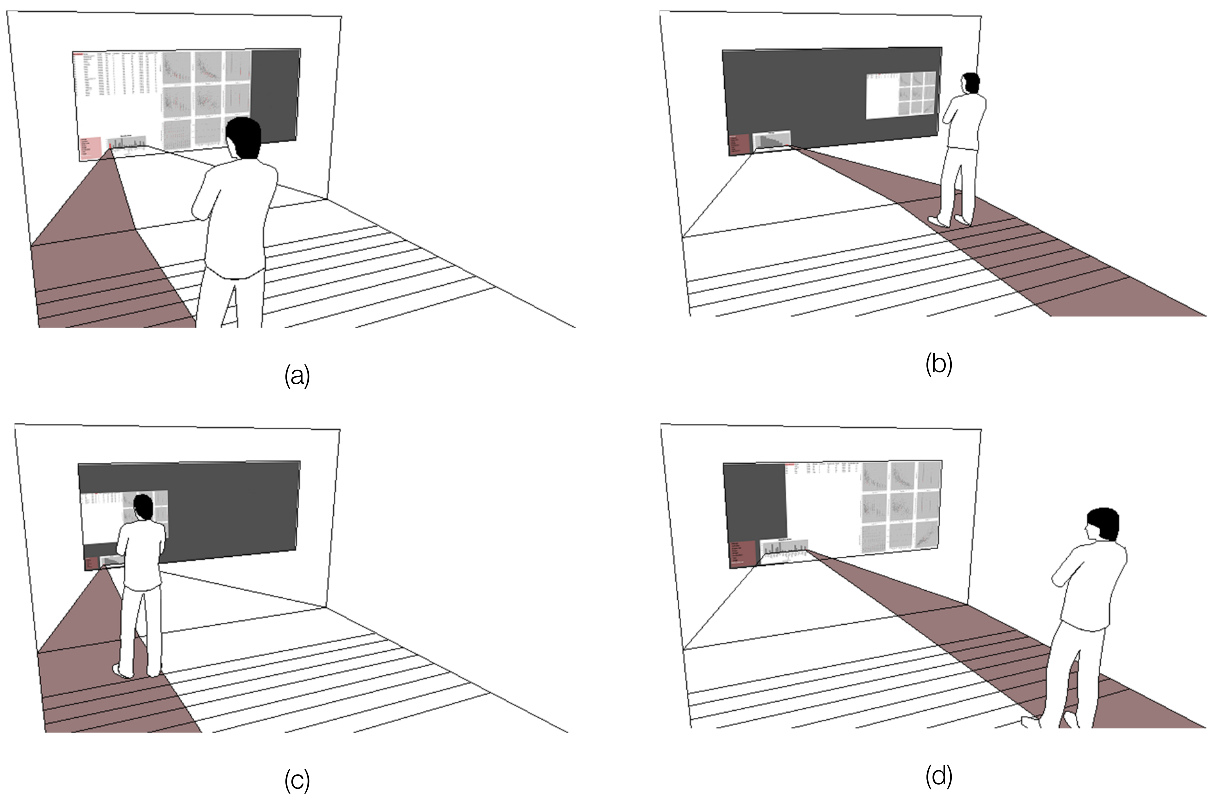


Figure 5.3: Techniques used in Design #3: Distance-dependent selection of filter attributes and scaling of abstract visualizations. Filtering is controlled by lateral movement. In (a) and (d), the user is distant from the display, resulting in large views. Correspondingly, the table and views are filtered and highlighted by car manufacturer. In (a), “AMC” is selected, whereas in (d), “Volkswagen” is selected (AMC corresponds to left and Volkswagen to right with lexical sorting in histogram). In (b) and (c), the user is near the display, resulting in small views. Correspondingly, the table and views are filtered and highlighted by mileage. In (b), cars with low mileage are selected, whereas in (c), cars with high mileage are selected.

to the display. We scaled the views according to distance, to enable users to read data while moving. Figure 5.3 (b to c) shows this. In addition, the window that contained the table and the scatterplots was positioned according to position. The other views remained fixed.

5.1.4 Summary

The three designs that combined visualizations on large displays with proxemics based interactions showed: First that it is possible to design and implement meaningful combinations from these two fields; and second that these designs may be useful with large displays.

5.2 Studies

As I briefly described above, we evaluated the three interface designs in formative lab studies. In the studies, we compared the novel interaction techniques to mouse-based interaction techniques. Each interface design was evaluated with six participants (often recommended for formative user studies [105]) aged between 23 and 37 years (M = 29.8), in sessions of approximately an hour per participant. While a study with six participants gives low power (in the sense of being able to detect quantitative differences) it allowed us to gain qualitative insights about usefulness. We compared the novel interaction techniques to a mouse-based interaction technique because previous work has suggested that participants generate more comments when exposed to several alternatives than to just one [144]. While the studies were formative, we asked users to solve predefined tasks that were adapted from previous studies of information visualizations. The idea was to ensure that they engaged in demanding tasks to experience and be able to discuss the usefulness of the interaction styles.

The studies aimed to provide initial, qualitative data about usefulness by having participants use and compare designs. The studies were lightweight and formative (i.e., qualifying and developing design opportunities rather than finding a "best" option). This choice of method requires justification. The overall aim of the paper was to explore design opportunities. We therefore decided against running a controlled experiment, as done in many evaluations of information visualizations and of proxemics [74, 166]. Instead, we wanted to gain empirical insight on a range of design possibilities. We also wanted to avoid rushing to experimentation (as warned about by e.g., Greenberg & Buxton [54]). We decided against some of the other methodologies for evaluating information visualizations [26] because they mostly assumed a hi-fidelity and well-defined design or required a specific application domain, task set, or user base. The former was not the case for the combination of information visualization and the novel interaction techniques, and the latter seemed to constrain finding and developing design opportunities.

We collected qualitative data from the studies. In addition to capturing preference data, at least two persons observed users while interacting: the observers took time-stamped notes that could be referenced and coupled to video recordings during analysis. We interviewed participants after trying both the novel and mouse interface, to learn about their experiences and thoughts about the novel interaction techniques. After completing all the tasks, we interviewed participants about each of the forms of interaction provided by the novel interfaces (e.g., distance and orientation).

We analysed each study immediately following its last session using the Instant Data Analysis technique [84]. For the analysis, we gathered in front of a whiteboard. Observations and interview comments were discussed. When we identified an important issue, we wrote it on a sticky note and fixed it to the whiteboard. We categorized the notes into themes. Based on the themes, we noted the most important findings with clear references to the observations and any supporting video recordings. On average, the analysis session lasted around two hours.

Next, I present the findings that emerged from these analyses.

5.3 Findings across the three interfaces and studies

In the following, I present the findings across the three studies that emerged from these analyses.

5.2.1 Subjective preferences for bodily interactions

Participants in all studies talked positively about using body movements to drive interactions for information visualizations.

In study 1, participants said they liked controlling map navigation with their body: it is a *"nice concept to use your body to move"* and *"it is nice that you move a lot, particularly in a work environment"*. Two participants mentioned that movement was intuitive, three that movement required less effort than the mouse, and two perceived movement to be faster than using the mouse. Participants were split in their preferences for the two movement-based techniques (absolute: 3; relative: 2; one undecided). Two participants commented that the absolute technique was intuitive, in particular because there was a direct relation between movement and what happened on the screen.

In study 2, participants described using distance as natural, intuitive, and making good sense. One participants said it was *"natural to use the body"*, another that it was *"intuitive to get more information in less space when up close. It works very well".* A third participant said in relation to aggregation of data with increasing distance that *"it was nice that there was not much data when standing back."*

In study 3, participants said their liked the idea of mapping physical space to data space. After having used both conditions, one participant said: *"Distance for selection of variables seems very natural*"; another described it as fun, although he felt more efficient when using the mouse. Participants however, were split on preference for using movement- or mouse-based interaction, and all suggested combining the two forms of interaction, one reason being that they could change variables using the mouse.

These results showed that participants could see the usefulness of driving information visualizations using bodily movement. This reiterates the findings presented in Paper I, that movement has potential to be used to implicitly or explicitly drive interactions with visualizations on large displays, and that people might find such interactions useful and perhaps even natural.

5.2.3 Movement and thought

Participants in the three studies gave comments and we observed interactions that had to do with task planning and execution, mental effort and spatial memory.

In study 1, participants used physical movement to structure tasks. Several participants moved to the back of the room in preparation for receiving the next task. In particular, one participant transformed the navigation task of finding and clicking an object at high magnification to a smooth movement from the back of the room (zoomed out) to the display (zoomed in). This suggests that movement-based interactions might support people in planning and executing tasks. Likewise, it suggests movement-based interaction might lead people to use suboptimal strategies.

In study 2, participants self-reported varying levels of required mental effort in using proxemics-based interaction. For example, a participant stated that although it was natural to move, using movement to interact with the visualization required more mental effort while moving, than using the mouse. In contrast, several other participants in the same study seemed to change easily between representations by moving. In particular, we observed three participants that moved back and forth repeatedly to switch between representations for solving tasks that involved relating homes or districts to municipalities. Changing representations using the mouse seemed less fluid, and participants glanced more often at the slider shown at the left of the display. In relation to aggregation of data with increasing distance, one participant said that the low amount of data was nice when standing back, which suggests that less mental effort was required to read the visualization.

In study 3, participants used physical descriptions of the data space. For example, one participant said "*Let me see what is out here*". Another participant said that he "*was in kind of a lane where [he] could filter instead of clicking with a mouse*", adding, "*It feels navigable*", and considered that the way he had the attributes mapped to the floor space, he would be able to "*go to cars with large engines*".

These results indicate that when using large displays, people may naturally use the space in front of displays to structure tasks, and to interact implicitly and explicitly with less effort by using movement compared to traditional interaction techniques (i.e., mouse and keyboard). It also indicates that people might map concrete physical spaces to abstract data, which visualization designers might use to support interaction and thinking.

5.2.2 Free or constrained movement

Participants in the three studies felt constrained, which was in contrast to be able to move freely. Some participants suggested solutions to alleviate these problems by temporarily disabling or locking interactions based on proxemics.

In study 1, participants talked about the freedom to move around, which they experienced differently for the two proxemics-based interfaces. With Absolute, one participant found *"a lot of freedom to move all over the place"*; in contrast with Relative, two participants felt *"restricted"* and unable to *"move freely"*. In contrast, participants liked the Relative interface for several other reasons. One participant reasoned that *"zooming was nice here"* because one could zoom without getting too close to the screen; when using the Absolute interface, participants zoomed by moving close to the display. One participant mentioned the benefit of a stable centre, in contrast to the Absolute interface where the display was changing much of the time. However, with the Relative interface participants had to keep track of their position relative to the centre. They described how you were "*fixed to the centre"* and that it *"required concentration to keep track of zones"*.

In study 2, we observed participants' difficulty in finding and staying within discrete distance zones. This resulted in abrupt attribute changes, and thus confusion. These observations were confirmed from participants' comments. To see certain information, participants were bound to certain distances. From our observations this was a problem for one participant in particular, who said that it was *"natural to step back for overview, but then the data [he] want[ed] to overview disappear[ed]."* In the mouse condition, this participant solved the tasks while standing noticeably farther from the display than the other participants. He for example, read details about individual homes from around 1.5m distance. Other participants made related comments. A participants for example said that you have to get close to see details on individual homes, but then *"up close, [he] had trouble keeping an overview of it all."* Another said that she had to remember to stand still at a distance.

In study 3, we observed that participants had problems in finding and staying within discrete distance zones, in particular that participants drifted when moving sideways to brush histogram bars. Participants suggested locking the position tracking to be able to approach the display or step back from it, without affecting the display state. A participant said *"[I would like to] be able to lock such that I can walk closer to something and then unlock it again"*; another that *"[I would like to] be able to lock variable choice…"* A participant demonstrated this by taking off the tracking cap so that he could move without changing attributes. The scaling of visualizations according to distance also confused participants. One participant got confused when pointing at the scatterplots, because it scaled when he walked closer to the display while doing so. This effectively locked the participant to a given position to be able to point in a workable manner. In the baseline condition, several participants moved closer to the display to point at data, which suggest that scaling, at least for some visualization techniques, is unviable.

These results first of all indicate that it is quite possible to construct poor designs, that seem sensible in the design phase, but clearly fall through even in lab use. Particularly, they suggest that it is problematic to use head orientation in the sense of continuous input mode, although might still be useful as part of a larger interaction space, or implicit interactions (e.g., use gaze direction as input to degree-of-interest functions).

5.2.4 Unnatural movements

Participants in the three studies both were observed to, and talked about how they moved in unnatural ways.

In study 1, some participants moved very slowly and some expressed uncertainty about the size of steps to take. It seemed to be difficult for participants to use their body movement for fine-grained navigation, in which it is harder to stop panning compared to using a mouse, perhaps due to inertia. Some participants adopted particular movement strategies, presumably to deal with these difficulties. Three participants leaned rather than moved to control location; two participants kept a foot in the centre of the Relative condition while lunging forward or to the sides, which one participant likened to dance-mat games. In addition to position tracking, head pitch was used to pan vertically. This caused unintended panning when participants looked down, which made participants aware of their posture and head orientation, and thus potentially caused unnatural movements. Some participants suggested the use of alternative means for panning, for example by using mid-air gestures.

In study 2, most participants moved somewhat naturally to control aggregation level (i.e., based on semantic zooming), but it was difficult for participants to control the detail view by head orientation as we had designed it. The primary reason for these difficulties seemed to be that it was hard for participants to keep their head in a steady position. Thus, all participants said they preferred the mouse for selecting the area to show details. A reason for this might be that the combination of using body position and head orientation was confusing. Participants suggested different ways of improving the movement-based detail view. Three participants said that they wanted to use their hands to freeze the detail view or for selecting houses, when they were within reaching distance. In addition, two participants suggested leaning close to freeze the details view. This suggests that details on proximity, or using head position relative to body position, may be a promising design variation.

In study 3, participants moved cautiously, often while looking at the histogram. We expect their focus on the histogram was partly to orient themselves to the discrete distance zones and histogram bars. The problems described in the previous section may have induced the cautious movements, in that participants had no method to freeze or lock to a particular zone. A participant said "*[I would like to] be able to lock variable choice such that [I] don't change in error, when [I am] busy*". Another reason for the cautious movements was that scale and position of views depended on participants' location. Thus, participants had to remain in a fixed position to read a visualization. Four participants said they disliked how this made them feel fixed to their position. They suggested instead a fixed scale (and using a locking mechanism as suggested above to be able to look closer at an item). Alternatively, three participants suggested improving the location-dependent scaling and positioning by using discrete steps, thus reminding of the selection of data and attributes.

These results shows that body position, although described as useful by participants, can also make people move in unnatural ways and impart a feeling of being fixed to a position. Thus, it suggests that designing explicit movement-, orientation- and location-based interactions should be considered very carefully, to let people use them in ways that are based on their natural movement and motor skills.
Specifically, with abundant display space, people will want to move to and from the display. Thus, it seems important to allow people to lock and unlock body-based interactions using e.g., mid-air interaction techniques, to enable people to do just that.

5.3 Summary and conclusion

In this work, we identified design opportunities and presented empirical findings from formative evaluations of three prototypes, which we compared to baseline conditions. Among other things, the results showed promise for changing zoom level or visual representation with the user's physical distance to a large display. Above, I presented four themes that we observed across the prototypes:

- Subjective preferences for bodily interactions
- Movement and thought
- Free or constrained movement
- Unnatural movements

These themes illustrated participants' subjective preferences for bodily interactions, how they used these interactions to plan and execute tasks, how they influenced participants' cognitive effort (self-reported), and how they used the physical space to describe data and data operations. However, the bodily interactions also presented limitations to participants. They often moved less naturally and felt more constrained.

We showed several possibilities for using position and movement to interaction with information visualizations. From the designs and evaluations it is clear that many additional opportunities exist, and that there is potential in applying such techniques to interacting with information visualizations. I return to discuss these in Chapter 8.

Chapter 6

Paper III
F3: Fast, Fluid, and Flexible Data Analysis on Large and High-Resolution Touch Displays

S. Knudsen & K. Hornbæk

Abstract – While large, high-resolution displays with touch are becoming available, visualizations on such displays rarely use expressive gestures and abundant display space. This paper describes F3, a system tailored for data exploration with touch on large, high-resolution displays. The design of F3 was informed by inquiries with a group of domain experts that analyse healthcare data. The touch interactions let users create new visualizations and combine parts of existing visualizations. After introducing F3, we present two studies of the system. First, we evaluated the usability of F3 in a laboratory study. Results suggest that users were able to use F3 for data exploration and that they valued its ease of use. Second, we evaluated the utility of F3 for data exploration in a field study, where the group of domain experts used the system over two weeks. The field study shows that the domain experts could construct hypotheses, and generate and execute strategies quickly — supporting ad hoc discussions and question answering during meetings. These findings contrast domain experts' descriptions of hours of trial-and-error with their current tools.

My contributions to Paper III

I carried the main responsibility of designing the F3 system, and all responsibility of implementing it. I also carried the main responsibility of designing the studies of F3. My supervisor, Kasper Hornbæk contributed to the design of the F3 system, as well as the study designs.

I was responsible for all parts of data collection and development of theory based on the collected data by running the lab study sessions, being present at the deployment site every day of the deployment study, and subsequently analysing the collected data, all of which are described in the following. My supervisor, Kasper Hornbæk contributed to data analysis through verbal and textual discussions.

I wrote the first draft of the paper and drew all figures. Both I and Professor Kasper Hornbæk contributed with subsequent revisions to the draft.

In the third paper, we were inspired by the way, in which participants in the first study had imagined using display space to spread out visualizations, to create new visualizations from existing visualizations, and to show these visualizations' relations with trails of thought. Other work in human computer interaction and information visualization supported the participants' ideas and inspired us to move further (e.g., [37, 143, 156]). The focus of our work was to design touch interaction techniques for creating new and combining existing visualizations. Our goal was to explore how abundant display space could change the possibilities for interacting with visualizations.

We developed the ideas based on long-term collaborations with a group of healthcare data analysts. The group of analysts perform analysis and documentation for a nation-wide healthcare organization comprising about 50 public hospitals, serving around 6 million citizens, and handling about 13 million patient contacts annually. Collaborating with the group of health care data analysts reinforced our avenue of research, and provided a natural case for developing and evaluating the ideas. As part of the collaboration, we made inquiries with the group to understand their domain of work. We based these inquiries on observing and interviewing them while working. The group also participated in the study described in Chapter 4 (see Table 4.1, group A and C). This gave us more insight in the domain, and the design possibilities. These methods enabled us to design a set of interaction techniques grounded in this domain. The goals of the techniques were to ease collaborative explora-

Paper	Aim	Method	Collected data	Analysis	Medium	Participants
III	Understand domain	Observation and contextual interviews	Notes, audio capture, photos, domain documents, data extractions, …	Ad hoc	Context of work	~ Domain experts
III	Design	Sketching workshops	sketches, photos, and notes	Ad hoc	-	Domain experts
III	Design	Evaluating mock-ups	Notes	Ad hoc	Large touch display	~ Domain experts
III	Evaluate conceptual model	Formative evaluations	Observation notes	Ad hoc	Large touch display	No specific background
III	Evaluate conceptual model	Formative evaluations	Observation notes	Ad hoc	Large touch display	Domain experts
III	Lab study	Formative evaluations	Observation notes	Instant Data Analysis	Large touch display	No specific background
III	Deployment study	Observations	Observation notes and audio capture	Affinity diagramming	Large touch display	~ Domain experts
III	Deployment study	Usage logging	Logs of use	Post-hoc data analysis	Large touch display	~ Domain experts
III	Deployment study	Semi-structured interviews with access to studied system	Observation notes and audio capture	Affinity diagramming	Large touch display	Domain experts

Table 6.1: Overview of study methods. Row 1 to 3 outline design work which I provide an overview of in Section 6.1. Row 4 and 5 outline the formative evaluations, which was based on a preliminary version of F3. These evaluations inspired me to conduct the study described in the Chapter 7 (Paper IV). Row 6 outlines the formative lab study (Study #1) which is described in Section 6.4. Row 7 to 9 outline the field study (Study #2), which is described in Section 6.5.

tion of large data sets by enabling creation and combination of visualizations. We strived for techniques that are fast, in that actions have a short interaction time span, giving immediate reactions to interface actions rather than showing intermediary menus; fluid in that the system state is clear and prompt feedback is given on interaction choices; and flexible in that system elements can be combined and results obtained in many ways. Table 6.1 provides an overview of the participant-based methods used in the studies. Note that I mainly focus on the studies marked with a grey background. However, while I do not focus on the formative evaluations shown in row 4 and 5, which was based on a preliminary version of F3, these evaluations inspired me to conduct the study described in the Chapter 7 (Paper IV).

The interaction techniques provide a novel approach to querying multi-dimensional data, and support drilling down, filtering, and grouping data. We designed the interaction techniques for bar charts and based their design on direct manipulation. Our idea was to enable analysts to combine database queries using visualizations of previous database query results through touch interactions. In designing the interaction techniques, we aimed to provide freedom in choice of analysis strategy. This benefits experienced analysts [36], and enables users to collaborate while constructing hypotheses, generating strategies, and executing them quickly, thus supporting ad hoc discussions and question answering during meetings.

I chose to include most paragraphs of Paper III in this chapter. I chose this approach, because I believe that Paper III is very compressed, and its results would benefit from more explanation. In doing so, I provide additional considerations throughout. Additionally, I have chosen to provide figures that more closely match the domain for which I designed F3. The included paper paragraphs are marked with vertical lines to the right of the respective paragraphs.

6.1 F3: Fast, Fluid, and Flexible

We named the system F3: Fast, Fluid, and Flexible. F3 provides touch interaction techniques for visualizations on large displays.

6.1.1 Domain

To inform the design of F3, we conducted observations and contextual interviews [15] over two weeks at the health care analysts' site to obtain a thorough understanding of their tasks. The first row (understand domain) in Table 6.1 shows this work. Isenberg et al. [71] and Carpendale [26] argued for qualitative methods in designing and evaluating information visualizations. We returned to the site for shorter day-visits throughout their work year to understand how their work changes in the course of a year. The analysts' work reminds of tasks and contexts characterized by Kandel et al. [82] , and their level of expertise falls somewhere between *hackers* and *scripters*.

The group of analysts comprise about 10 employees, and are part of a group of about 35 employees that work with documentation of healthcare services. They have mixed backgrounds, including economics, political science, mathematics, statistics, medicine, public health science, and computer science. They primarily use SAS, SQL, and MS Excel for data analysis. They use visualizations to understand data in Excel (e.g., bar charts, line charts, and scatterplots), and communicate data externally in static documents and with QlikView.

Domain Tasks and Data

The health care analysts receive data from all national hospitals at regular intervals. The data is primarily used to compute rates for hospital treatments (diagnosis related groups [46]), which are based on matching hospital activities data to expenses. They publish these rates annually, enabling the government to use these rates as basis for compensating individual hospitals based on their workload. Figure 6.1 shows an overview of these collaborations and computation processes.

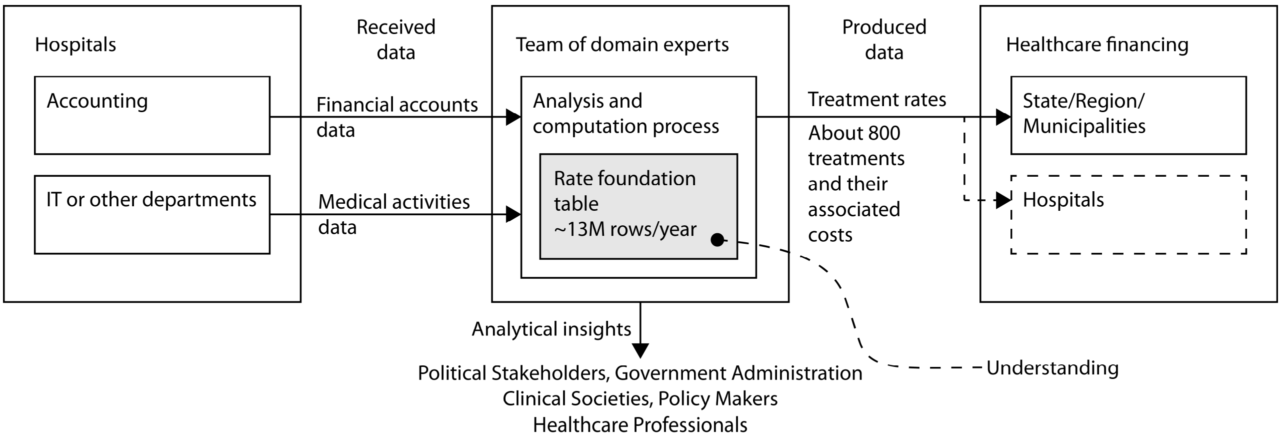


Figure 6.1. The analysts' collaborations and computation process.

The received data comprise medical activities and financial accounts data. Medical activities data describe what has happened at a hospital (e.g., patient admittance and discharge dates from the wards and blood test meta-data from clinical biochemistry). Financial accounts data describe the expenses incurred at a hospital (e.g., doctor and nurse salary expenses for each hospital department, implant costs for each department, and overhead costs). To compute the rates, the analysts establish the rate foundation table, which combines the medical activities and financial accounts data. The table contains a row for each patient (~13M/year). Each row describes a patient contact (an admission and discharge for inpatients and comparable information for outpatients), and comprise columns of patient information (e.g., age, gender, diagnoses), treatment information (e.g., procedures, duration, ward, hospital), and cost information (e.g., diagnosis related group, salaries, overhead). The domain data comprises for example: (i) codes describing operation procedures in a hierarchy of about 9.000 codes; (ii) hospital and ward definitions in another hierarchy of about 20.000 wards, that describe physical locations that change both name and id over the years; and (iii) admission and discharge data that were supposed to span two years, but spanned 44 years due to data registration errors.

The analysts' work is characterized by constant adaptation to changing healthcare policies. This means that the data they handle change on a yearly basis. New information codes are added and existing codes may be changed or removed. Changes include addition of administrative patient pathway codes, combinations of codes describing in- and outpatients, and introductions of new medical procedures, thus requiring new description codes.

Thus, a large part of their work lies in data wrangling [82], in that they need to adapt their existing data flows to changes, and understand where errors have occurred in the process.

Context of Work

The health care analysts work in an informal work environment dominated by three- to four person offices. They frequently interrupt each other with quick questions such as "*do you remember the code for the new cancer treatment?*" Additionally, pairs of analysts meet daily to weekly for scheduled one to two hour analysis meetings in front of a computer to work on a shared task. The analysts also hold weekly group analysis meetings with their manager to discuss ongoing work. Their current analysis meeting practice is, to present data and analysis problems, note questions and comments, and return to their desk after the meeting to continue their analysis based on the received questions and comments. For example, when presenting analysis problems during such meetings, other participants questioned whether an analyst had "*look[ed] into whether they [the data] all contain implants?*" which would require the analysts to return to their desk after the meeting to answer the question.

The process of setting treatment rates (diagnosis related groups [46]) involves communications with external political stakeholders such as clinical societies, policy makers, and regional healthcare professionals. Collaborating with these diverse groups requires communication of complex data to people who have limited experience with data analysis.

The various stakeholders have their own political agendas. For example, the clinical societies aim to advance the focus of their specific medical specialty, and the rates associated to it. During interviews, the analysts have described their current collaboration with the clinical societies as an *"endless series of meetings and email exchanges that take the form of negotiations"*.

In addition to the yearly task of computing rates, the analysts work on shorter tasks to support internal and ministerial political functions, as well as researchers, journalists, and law enforcement, who all share an interest in obtaining knowledge from the data.

Design work

From these inquiries with the health care analysts, we became interested in supporting parts of their work with quicker, collaborative, ad hoc data exploration tools. As part of designing F3, we conducted design workshops, and evaluated lo-fi prototypes and mock-ups with the analysts. The second and third row (design) in Table 6.1 shows this work. During our collaborations, the analysts worked creatively with us to come up with novel interactive visualization designs. Participants in the design workshops for example considered support for exploring why the number of patients admitted for specific treatments dropped from one year to the next and analysing the cost distributions of specific treatments across hospitals.

Before using F3, the analysts were accustomed to discuss data analyses during meetings, and to look at data individually. With F3, the goal was to let the analysts discuss data analysis problems while interacting with the data. We imagined the analysts could use F3 to collaborate while constructing hypotheses, generating strategies, and executing them quickly, thus supporting ad hoc discussions and immediate answers to questions about data during meetings.

Thus, we designed and implemented F3, which I describe in the next section, to support the analysts' data exploration tasks.

6.1.2 Design Goals

The goals of F3's interaction techniques were to ease collaborative data exploration of large data sets by enabling fast, fluid, and flexible creation and combination of visualizations.

F3's interaction techniques provide a novel approach to querying multi-dimensional data, and support drilling down, filtering, and grouping data. In designing the interaction techniques, the aim was to support data exploration by enabling fast, fluid, and flexible interactions on data:

Fast: User interface actions have a short interaction time span. In designing F3, we aimed to provide immediate reactions to interface actions rather than intermediary menus. The argument is that it allows users to quickly gain an overview of datasets and obtain valuable insights. In addition, a data cube store pre-computed aggregations (see next section), such that even complex queries return fast results.

Fluid: The user interface provides continuous feedback and invite for unbroken series of interaction. In designing F3, we aimed to provide feedback on possible choices and the state of the system, and ensure that results of actions open the possibility for new interactions. This for example means that F3 gives feedback on possible release locations similar to tableau [168] when users drag user interface elements and that it is possible to interact with many parts of visualizations.

Flexible: The order and approach to data exploration is flexible. In designing F3, we aimed to create interaction techniques that allow for variation in data exploration. For example, there are many possibilities and ways of combining user interface elements to produce different outcomes and users' can accomplish many goals in several ways.

In designing F3, we wanted visualization components and data fields to be able to be touched and dragged onto as many elements in the user interface as possible. For all combinations, we reviewed how well they supported the required low-level visualization tasks.

We aimed to provide interaction techniques that support what Brehmer & Munzner [21] described as data *discovery*, *exploration*, and *comparison*. They described these as the reason users conduct a task (i.e. why). We supported these intentions primarily with *manipulate* and *introduce* interaction techniques. Brehmer & Munzner described these as the manner in which users conduct a task (i.e. how). When using F3, users create many related visualization views, which F3 show with line connections. Thus, some of F3's interaction techniques focus on changes within views and some on changes between views. Therefore, in the task typology, some of F3's interaction techniques focus on supporting *manipulation* tasks, while other focus on supporting *introduce* tasks.

As part of designing F3, we conducted a small lab study with three participants. In the study, we asked participants to analyse a small data set about cars. In the study, we observed participants' uncertainty about the relations between views. This observation led to F3's representation of parent-child relations, which I describe in section 6.2.

We designed the interaction techniques with inspiration from design guidelines for post-WIMP user interfaces [40, 90] (e.g., consider feedback, reduce indirection, and integrate UI components in visual representations). We also aimed to enable users to use both hands in a single task (e.g., to select an item as context for another, see [57]), or in simultaneous tasks (e.g., do two similar actions at once).

The interaction techniques in F3 can be adapted to many visualization techniques. For F3, we chose to focus on bar charts. The analysts that we designed F3 for, are familiar with bar charts, and use these often. Additionally, bar charts display aggregate information, and therefore apply well to the visualized domain data. I return to discuss the applicability of the interaction techniques to other visualization techniques in section 6.6.4.

6.1.3 Data Model

We designed F3 primarily to help the health care analysts understand the rate foundation table, which I described in section 6.1.1, and its potential data errors. The rate foundation table is multi-dimensional and contains highly hierarchical data. Constructing an OLAP cube [53] based on the rate foundation table, facilitates slicing, drilling down, and pivoting according to any of the tables' columns to enable detailed data exploration and analysis.

We based F3's visualization and interaction techniques on the data cube model. This helped facilitate meaningful results from combinations of user interface elements. The core parts of the model consist of *dimensions*, *levels*, *members,* and *measures*.

Designers of OLAP cubes often map nominal data columns in a data table to *dimensions*. For example, the often map, year, month, and day columns to a date dimension. These are *levels* of the date dimension hierarchy, and instances of these levels are *members*. For example, a date dimension may contain year as a level, which contains 2013 as a member. F3 encodes dimensions with data bars' horizontal position in bar charts.

Designers of OLAP cubes often map quantitative data columns in a data table to a *measure*. For example, they often map costs to a measure. Measures contain aggregates of raw data columns, grouped by dimensions. F3 encodes measures with data bars' height in bar chart. To be able to construct histograms, it is useful to bin some measures, for example to construct a histogram of costs. Therefore, the data model can contain data fields, which are possible to use as both measures and dimensions. I refer to these as binned measures.

Previous information visualization research have used the data cube model to support data exploration and analysis (e.g., [39, 138, 168]).

Interaction Technique	Section	Action	Result	Complexity
View Creation	6.2.2	Drop a data field on the canvas	A new view	Simple
View Configuration	6.2.3	Drop a data field on a view's axis	The view's axis is re-configured	Simple
View Cloning	6.2.4	Drag a view with two fingers	A clone of the view	Simple
View Synchronization	6.2.5	Drag views so that they overlap, then tap button	Y-axes in the two views use the same scale	Simple
View Exploration	6.2.6	Drop a data bar on the canvas	A view drilled down on the data bar	Intermediate
View Filtration	6.2.7	Drop a data bar on a view's filter area	The view is filtered based on the data bar	Intermediate
View Exploding	6.2.8	Drop a data field on a view's explode area	Views for each of the data field's members	Intermediate
Trail Cloning	6.2.9	Hold data bar, while clone dragging a child view	A clone of the trail between data bar and view	Complex
View Matrix creation	6.2.10	Drag views so that their corners overlap	A matrix of views combining the views' axes	Complex

Table 6.2. Overview of interaction techniques.

6.2 Interaction Techniques in F3

The interaction techniques in F3 support creating visualization views by combining, extending, or re-using existing visualizations. In doing so, the techniques provide a novel approach to querying multi-dimensional data and receiving visualization views as query results. Table 6.2 presents an overview of the techniques; Figures 6.2 to 6.10 show them as sketches to improve readability. The first techniques are simple but necessary for exploring data; the latter techniques are more complex, and aim to help solve specific tasks. Next, I describe the basics of each technique, discuss design alternatives, and open issues.

6.2.1 F3 Interaction Concept

In F3, access to data happens through a data field menu in the top part of the display (see Figure 6.2). The menu shows dimensions and measures from the data cube model [53]. Users drag data fields from the menu and drop them on relevant parts of the user interface.

We opted to use a permanent and fixed position for the data field menu. As an alternative, we considered showing a menu when touching relevant parts of the user interface, but imagined that the chosen solution requires fewer instructions to get started, and thus work better for walk-up use.

Views are the main user interface element of F3. A view shows data in bar charts. The x-axis encodes dimensions and the y-axis encodes measures (see Figure 6.2). Users move views by dragging with one finger.

6.2.2 View creation

To create a view, users drag a data field from the data field menu and release it on the canvas (the background area), which results in a bar chart that shows the dropped data field (see Figure 6.2). We designed view creation with focus on speed and of ease of use, since creating a view is a necessary first step in most tasks, and thus frequently used. Because the dragged data field may both represent a dimension and a measure, the two possibilities provide slightly different results. A dragged dimension or binned measure results in a view that encodes the dragged field on the x-axis, whereas a dragged measure results in a view that encodes the dragged field on the y-axis. The axis not mapped by the released data field shows a default data field provided by the data model, which for the y-axis could be number of observations in the database. After creating the view, users may reconfigure views' axes, which the technique I described next facilitates.

F3 scale the y-axis according to the value of the maximum data bar of the displayed data (zero is obviously always shown). The maximum value of the axis is computed to be the smallest of *1*, *5*, or *10* multiplied by power(floor(log(*value of maximum data bar*)). This satisfies three criteria: (1) the scale and tick marks are easily readable, (2) the likelihood that different views use the same scale is high, and (3) data encodings use much of the space within views.

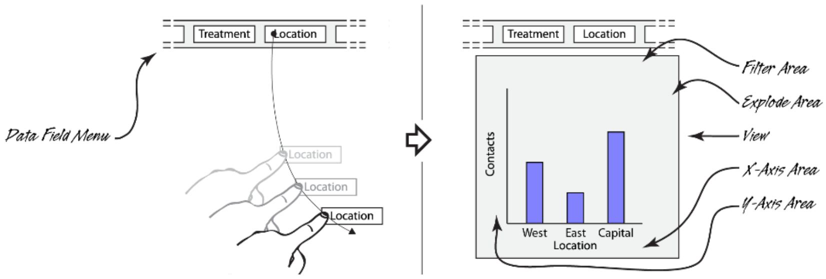


Figure 6.2. Drag data fields onto view axes to reconfigure views.

We opted to use a technique for creating views that requires minimal interaction and let the system provide default values for other potential choices. As an alternative, we considered a technique that would require users to drag two data fields to create a view. This would ensure that users were aware of axis mappings. We chose not to require this to provide as fast interactions as possible.

We designed *view creation* to enable users to quickly obtain high-level information about the data cubes' dimensions, and thus be able to construct an overview of data. For example, to see the distribution of patients across regions in Denmark, users simply drag out the *treatment location* dimension.

The quick and simple technique of obtaining high-level information about dimensions is similar to Tableau [168]. However, Tableau requires users to select both dimensions and measures to obtain a similar overview. We wanted to avoid this, and opted to define a default measure and dimension. This reduces the amount of interaction, potentially at the price of users' reduced awareness of the selected encoding.

6.2.3 View Configuration

To configure a view's axis, users drag data fields from the data field menu and release them on a view's axis label. This allows users to perform the most essential configurations of a view. It is possible to drop dimensions on x-axes, and measures on y-axes (see Figure 6.3). Dragging a data field over an axis highlights the release area, if the dragged field is compatible with the axis. Dropping the data field configures the axis. This provides users the opportunity to alter views as needed, and to select alternatives to the default selection. View configuration thus allows analysts to change the visual encoding of a view (i.e. *change* [21])

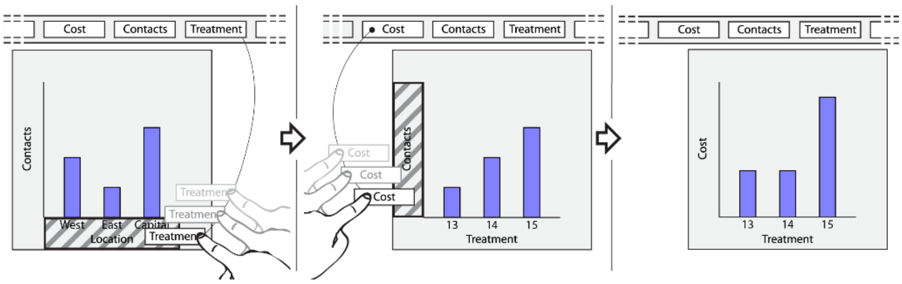


Figure 6.3. Drag data fields onto view axes to reconfigure views.

Other work has facilitated such choices by direct axis interaction. For example, Sadana & Stasko [122] let users tap an axis to see a list of data fields. Tapping a data field replaced the existing with the new one. This approach is equally valid, but to keep the overall design consistent across F3's interaction techniques, we chose not to provide this option.

Tableau [168] also uses drag and drop to configure axes, but facilitates both replacement and addition to the axis encoding. Tableau facilitates replacement by dropping data fields on axes, while dropping data fields on a special rows and columns area results in a more complex spatial encoding. This allows construction of increasingly complex visualizations, at the cost of less quick reconfiguration of existing visualizations. F3 facilitates data exploration through other means of interaction. Therefore, the need, and thus ability, to create complex visualizations within a view is smaller and a quicker reconfiguration of axes seems to be a better choice.

6.2.4 View Cloning

To create a clone of a view, users drag a view with two fingers (see Figure 6.4). This allows users to continue their exploration in a clone, for example by changing axis encoding, while the original view is preserved. We designed cloning to work similar to drag, and leverage the added efficiency provided by chunking [23] drag and clone interactions. To rearrange a view and create a clone, users start by dragging a view. Adding a second finger after positioning the original view, results in a clone operation. The user is then free to use one or two fingers to continue positioning the clone view.

F3 reserves two-finger and two-hand interactions for more advanced and infrequent interactions. We designed view cloning for single hand two-finger operation.

Because the idea of working with many views are integral to F3, we chose to provide a quick method to clone views. This is in contrast to many other systems. For example, some desktop-based systems allow copying visualizations by using copy and paste operations (e.g., Tableau [168]). This is a two-step process, and thus slower than F3. Lark [143] lets users create clones by dragging fingers from the visual representation of the information visualization pipeline, which is very comparable to F3. Where Isenberg et al. based Lark's technique on interacting with the information visualization pipeline, F3's technique is based on interacting with the view itself, which I believe offers a more direct approach.

We designed the technique to provide a way for users to preserve a view in the middle of an analysis, to use two alternative approaches to a data analysis, or to split an analysis into two comparable branches. For example, in analysing the cost distributions of a hospital, users might start from a view that encodes the number of patient contacts on the y-axis. Before configuring the y-axis to encode costs, they can clone the view to be able to refer back to the number of patient contacts.

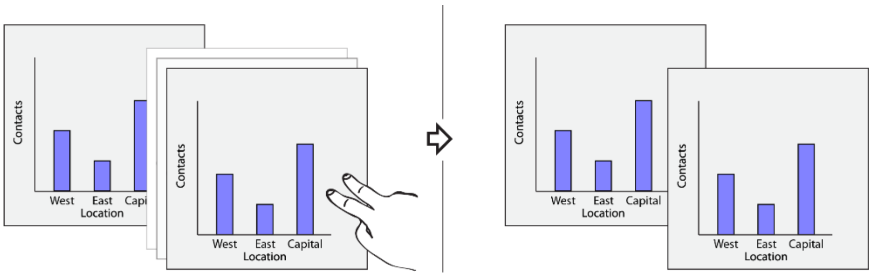


Figure 6.4. Drag views with two fingers to clone views.

6.2.5 View Synchronization

To synchronize views' y-axis scales, users drag a view such that its side area overlap another view's side area (see Figure 6.5). This helps users to compare views. When views that encode the same measure overlap, a synchronize button appears above the y-axes in both views. While holding onto the view, tapping the synchronize buttons with a finger from the other hand, cause the view in which the button was tapped to adopt the scale of the other view.

We designed the technique with the aim to reduce unintentional synchronizations while for example arranging views and to keep the design of the technique similar to the other techniques. We also considered if the technique should facilitate measure changes, but chose not to, to reduce chances of errors.

We designed *view synchronization* to enable users to compare views *side by side* as described in Chapter 4 (Paper I). By providing a way for users to scale views similarly, they can compare the views using the spatial encoding. For example, in comparing cost distributions for a large and a small hospital in two separate views, users can synchronize the scales. This allows them to compare the visualized data more easily, than if they had to compare data in the two views encoded with two different y-axis scales.

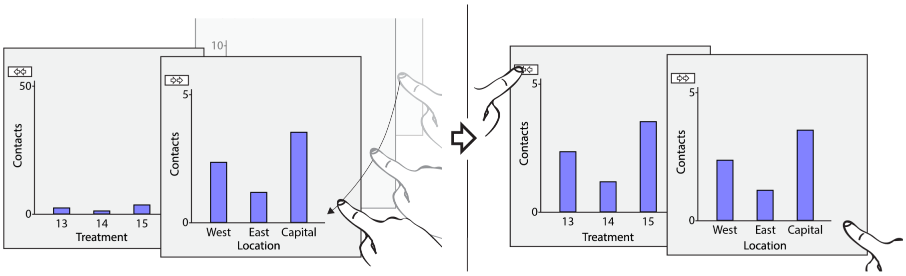


Figure 6.5. Drag views onto each other so that they overlap. A synchronize button to appears. Tapping it synchronizes the axes' scale.

6.2.6 View Exploration

To create a child view based on data represented by the parent data bar, users drag data bars out of a view and release them on the canvas (see Figure 6.6). This allows users to drill down and perform more detailed data exploration in a new view. The metadata necessary to provide a useful result is obtained from the data model that provides *child members* (e.g., 2014, September, or 22nd) at a *level* below the data bar (e.g., year, month, or day). F3 show these child members on the x-axis in the child view. In case no child members exist for the dragged member, the child view shows the dragged member.

To add additional data bars' child members to the child view, users drag these bars from the parent view and release them on the child's filter area, which is located above the data area. This allows users to select multiple items from a view to analyse in more detail. To show how the child view was created, a line represents the parent-child relation from the parent data bar to the child view's filter area.

As an alternative, we considered that releasing a data bar would result in a child view similar to that of the parent, but only showing the dragged data bar. Such a design would be easier to understand, but would require a greater number of interaction steps. In case no child members exist for the dragged member, this is the result.

Creating a series of views, in which each child is the parent of another child, shows a history of exploration steps. I described this theme as *trail of thoughts* Chapter 4. F3's parent-child representation does not rely on colour encoding, thus freeing colour encoding for other purposes. At the other end of the design spectrum, colour highlighting could completely replace the use of line connections, which might be sufficient as long as there are relatively few views. Since the aim of F3 is to support numerous views, it is better to use line connections to represent parent-child relations.

We designed *view exploration* to enable users to go into more detail with parts of data and to explore data. For example, in looking at the number of patient contacts per region, users can explore patient contacts in more detail within a region by dragging out the data bar for that region. This allows users to see patient contacts for hospitals within that region, while still maintaining the overview. Dragging another data bar out, allows users to compare the two regions in more detail.

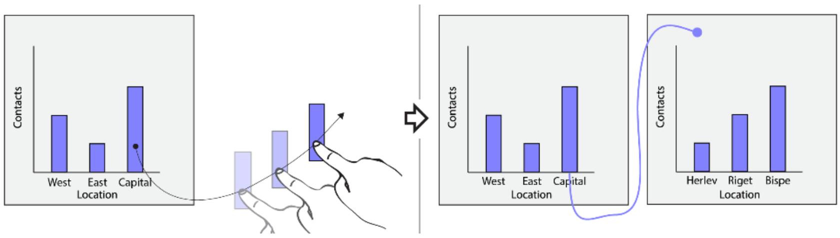


Figure 6.6. Drag data bars onto a views' filter area, to filter by the dragged data bar.

6.2.7 View Filtration

To filter data shown in a view, users drag data bars out of a view and release them on another, yet unrelated, view's filter area (see Figure 6.7). The technique works similarly to *view exploration*, and allows using views as filter palettes, thus supporting flexible exploration in other views. F3 highlights the filter area when users drag data bars to it. Additionally, it represents multiple filters on a dimension as a single circle. These are logically OR'ed. F3 represent filters on different dimensions as different circles. These are logically AND'ed. Because the design does not include range-queries, it is useless for two filters on the same dimension to be AND'ed. Flicking up or down on a filter circle inverts the filter. Similarly, flicking left and right on the filter circle enables or disables the filter (this also works for *view exploration*).

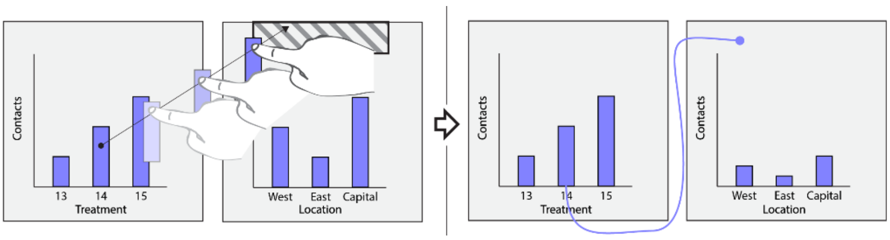


Figure 6.7. Drag data bars onto a views' filter area, to filter by the dragged data bar.

We designed *view filtration* to enable users to use parts of views to work with other views. On the surface, *view exploration* and *view filtration* appear similar. However, they support different tasks and approaches to data analysis. For example, in looking at a view that shows different pregnancy related treatment groups, users might want to see how the distribution among the treatment groups looks for patients at 30 to 39 years (30-year bin). Thus, they use the *create view* technique to create a new view that shows age distribution for the entire data set. Then, they drag the 30-year data bar from the new view and drop it on the filter area of the view showing the pregnancy related treatment groups. Flicking the filter on and off allows the users to compare the entire age span to that of the 30-year bin, and thus see views *one by one* as described in the *Juxtaposing* theme in Chapter 4 (Paper I).

6.2.8 View Exploding

To explode a view according to members of a data field, users drag data fields from the data field menu, and release them on a view's right-hand side (see Figure 6.8). This facilitates breaking down the original view by the dragged data field and comparing its different members to each other, similar to small multiples. The explode area is highlighted when dragging data fields on top of it. Releasing the data field generates views for each member of the dimension. The abundant display space allows member views of similar size and scale to the original view, which facilitates comparison.

The result of the technique is that the original view's area increases, such that it contains the original view, as well as the member views to the right of the original view. F3 shows members in a scrollable list if there are more than four members. F3 aggregates the members that scrolling hides, in a view to the right of the list.

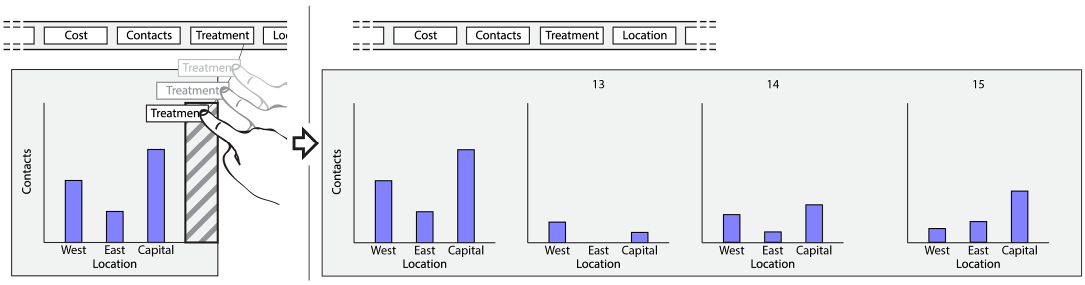


Figure 6.8. Drop data fields on views to create copies of the view, filtered for values of the dropped field.

Data bars from other views may be dropped on the explode area, just like data fields, to explode the view by child members of the aggregate represented by the bar. For example, dropping the data bar 2013 on the explode area, generates member views filtered on quarters of 2013.

We designed *view exploding* to enable users to see a view de-aggregated into parts by a selected dimension or data bar, similar to small multiples. For example, in looking at a view that shows different pregnancy related treatment groups, users might want to see how the distribution among the treatment groups looks for different patient age groups. Thus, they drag the *patient* age dimension from the data field menu and drop it on the explode area of the view showing the pregnancy related treatment groups, to see and compare the distribution of pregnancy related treatment groups across age groups *side by side* as described in the *Juxtaposing* theme in Chapter 4 (Paper I). This would for example allow them to analyse if certain treatment groups are more dominant for older patients compared to other patient age groups.

6.2.9 Trail Cloning

To clone an entire exploration trail, users hold onto a data bar in a parent view, while dragging a view using two fingers similar to cloning a view (see Figure 6.9). This facilitates comparisons between subsets of data, which may be useful, for example, when a user look at one part of data, and would like to see if other parts show similar patterns. When holding onto a views' data bar, F3 highlights trails of the view that users can clone. This sets the context for the following interactions. Using the other hand, two-finger dragging a highlighted view creates a clone trail. These interactions result in a new exploration trail that show views similar to those in the original trail. The interaction technique facilitates fast comparison between the two sets of data, in that users can create the new trail quickly, and provides fluidity, in that it is possible to perform the interaction as part of a longer series of interactions. F3 positions the cloned trail where users release the dragged view, and lays out intermediate views similar to the original views, which the right side of Figure 8 shows. F3 allows creating trail clones when all members between the data bar held on to and a child view exist in the potential trail clone.

The abundant display space provides the opportunity of showing many views. Trail cloning provides a fast way of creating them. In particular, the technique facilitates comparison between multiple comparable slices of data, which is a common data analysis task [4].

We designed *trail cloning* to enable users to create an analysis branch similar to a current branch, but with another basis. This enables users to compare parts of data. For example, in looking at age distributions of pregnancy related treatments (major disease code 14) in the capital region, users might want to see the same distribution, but for another group of treatments. Thus, they use two-finger dragging to clone the view that show age distributions, while holding onto another treatment group, to compare age distributions for the two groups of treatments (see figure 6.9).

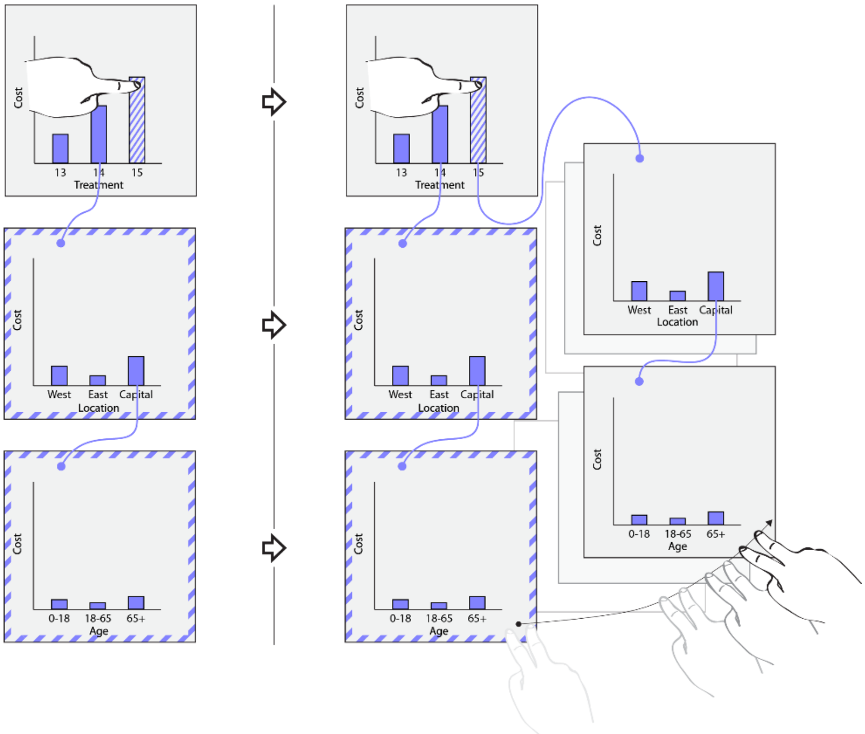


Figure 6.9. Trail cloning technique: An exploration trail can be cloned by holding onto a data bar in a parent view, while two-finger dragging a child view.

6.2.10 View Matrix Creation

To create a view matrix of the combination of two views, users drag one view's corner on top of another view's corner (see Figure 6.10). This allows users to relate and compare data in the original views. When a user drags the top-left corner of one view on top of the bottom-right corner of another view, F3 shows view matrix creation is possible by highlighting the views' corners. When the user releases the view, F3 creates a matrix that combines the two views' dimensions and measures. The source views keep their position within the matrix.

The number of rows and columns in the matrix depend on the dimensions and measures in the two source views. Dimensions that have no corresponding measure (e.g., fruit or hospitals), only fit on x-axes, and thus only on matrix columns. Likewise, unbinned measures only fit on y-axes, and thus only on matrix rows. F3 creates a 2x2 matrix if users combine views that encode such data fields. In the other extreme, F3 creates a 4x4 matrix if users combine views in which both axes in both views encode binned measures.

If the two views encode the same dimension and level on the x-axis or the same measure on the y-axis, then the views are incompatible and *view matrix creation* is not possible. If the two views are incompatible, F3 does not highlight the views' corners when users drag the views onto each other.

We designed *view matrix creation* to provide users with a shortcut to see combinations of two views. For example, in looking at distributions of costs and contacts across treatment groups and locations respectively, users might be interested in seeing the possible combinations of axis encodings. Thus, they drag the views' corners over each other, to obtain a view matrix (see figure 6.10).

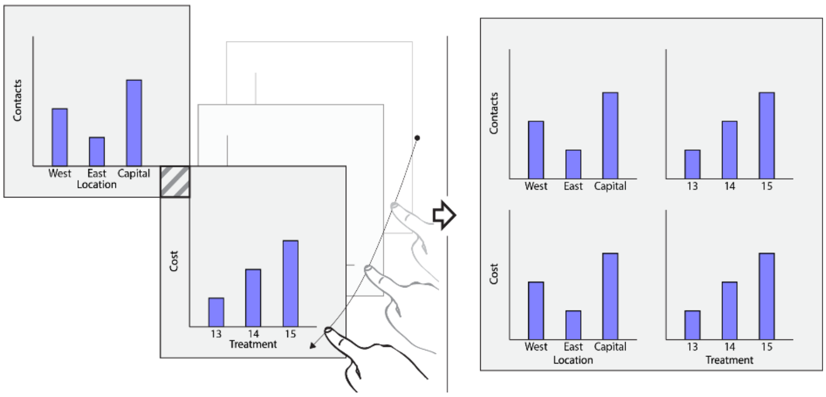


Figure 6.10. Drag view corners over each other to create a view matrix.

6.2.11 Combining the Interaction Techniques

In combining the interaction techniques, many questions arose. Particularly: how should F3 behave if users attempt to clone a view with a parent, to configure a view with children, to filter a view with children, or to flick the dot of a de-aggregation? In the following, I will describe these considerations.

When users clone a view, F3 clones all parent links and no child links as part of the interaction technique. This permits users to clone views with children, to enable them to continue working with them, for example, by configuring their axes.

When users drag a dimension onto an x-axis of a view with children, F3 does not highlight the x-axis, thus indicating that it is not possible to drop the dimension onto the axis. This is not possible, because this would remove the visual representation of the filters in any child views. However, a fast workaround is to create a view clone, which allows x-axis configuration.

When filtering a view with children, F3 also filter the child views. Similarly, when flicking the filter dot, F3 also reflect this in child views. This allows users to filter complex analyses after they have constructed a trail of views. For example, in looking at age distributions of pregnancy related treatments (major disease code 14) in the capital region, users might want to see data for only spontaneous births. Thus, they use the *create view* and *explore view* interaction techniques to navigate the hierarchy of diagnoses to find the data bar for spontaneous births. They drop this data bar on the filter area of the first view in their trail of views. This results in filtering the entire trail for spontaneous births, which can be turned on and off by flicking the newly shown filter dot.

When flicking the filter dot of a de-aggregation created by *view exploration*, the view simply shows all members at the de-aggregated level, thus allowing users to see more members in a view. For example, in looking at number of patient contacts across years, users might want to see patient contacts across months instead. Using *view exploration* by exploring a single year to obtain a view that shows months for that year, and then flicking the filter dot, shows months for all years in the data.

6.3 Implementation and Apparatus

We implemented F3 in Java using a combination MT4J [89] and the Prefuse data visualization toolkit [60]. Specifically, the Prefuse renderers where ported to MT4J where they generate and update MT4J components. The data and data model were stored in an MSSQL server and MSSQL Analysis Services cube respectively. F3 query the data using Olap4J (www.olap4j.org).

F3 work with different display sizes and touch systems. However, we conducted both of the studies that I describe in the following sections on a Smart 8084i display. Figure 6.11 shows analysts using this this display and F3 to explore age distributions of pregnant patients. The display has a spatial resolution of 3840x2160 (also known as 4k), a 30Hz refresh rate, measures 84 inches diagonally and supports four simultaneous touch points. An 84” display is sufficiently large to provide the experience of abundant display space, while it is still physically possible to move into busy offices and employees’ work area, which was necessary for the second of the two studies described next.

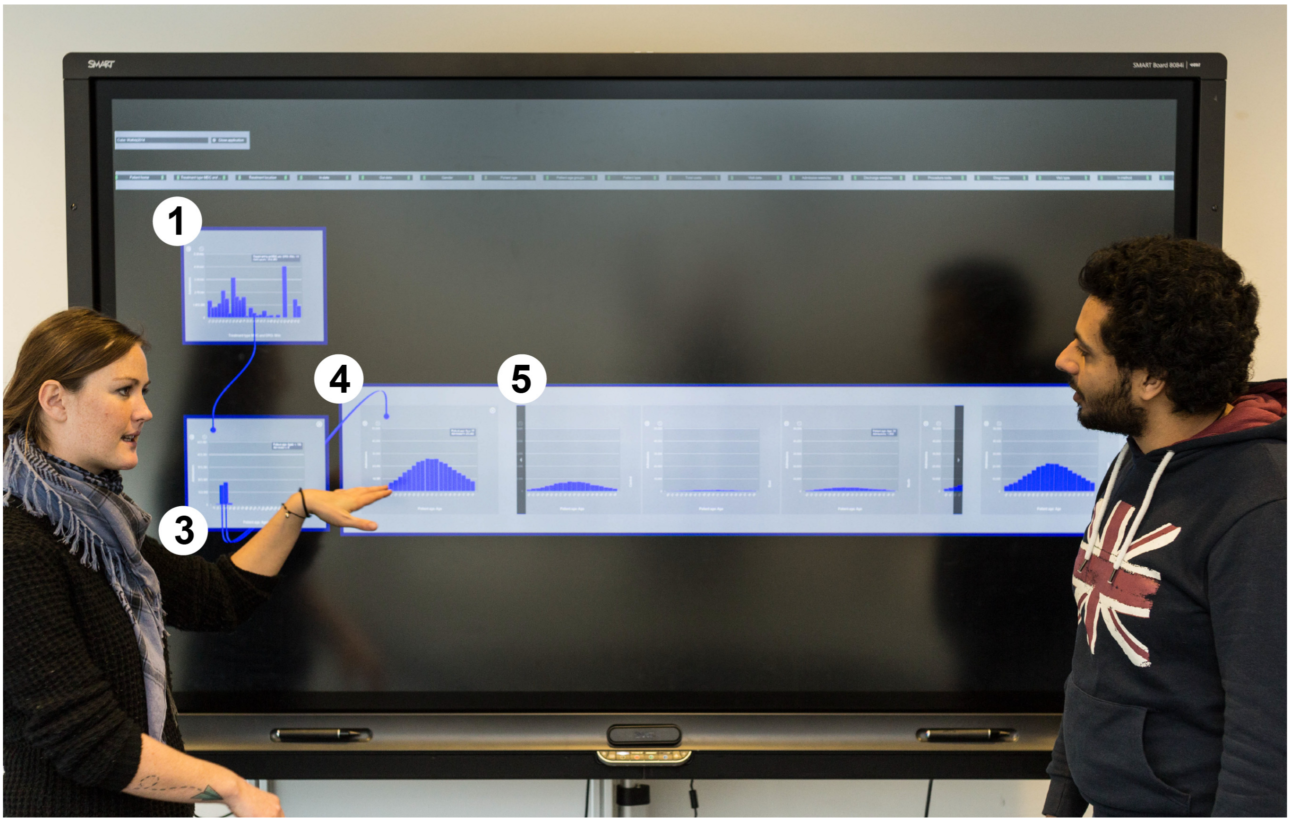


Figure 6.11. The photo shows how analysts using F3 to explore age distributions of patients admitted in relation to pregnancies. The photo shows: (1) they created an overview of treatments; (2) from this view, they explored treatment group 14, which relate to pregnancy and labour. This resulted in a view (not shown) showing different treatments of this group; (3) they reconfigured this view to show age distribution; (4) they explored the group of patients from 20 to 39 years, which resulted in another view; (5) they exploded this view by regions to understand how age compared across regions, resulting in the long view centred on the display in the photo, which shows that women in the capital region are older when they have children, compared to other regions.

6.4 Study #1: Formative Laboratory Study

The first study investigated usability issues and reactions from participants whom we asked to solve a range of data analysis tasks. The sixth row (lab study) in Table 6.1 shows this work.

6.4.1 Participants, Data and Tasks

We recruited nine participants (age: 27-57, mean 34). Participants were current or former Master-level students. They all conducted data analysis on a regular basis.

We used the rate foundation table that comprised nation-wide admissions, treatments, and expenses data for the years 2012 and 2013 as basis for the data cube that spanned 7 dimensions and 6 measures.

The tasks were developed from taxonomies of data analysis [21] and inquiries with the group of health care analysts (see section 6.1.1). I provide an overview of the tasks in Table 6.3. The first four tasks were brief and asked participants to answer factual information. The next two tasks were longer and required several interaction. The last two defined tasks were complex tasks that required for example data comparisons. We deliberately asked participants to work on clearly defined tasks, even though the goal of F3 was to support data exploration. We chose this approach to ensure that the system was useful before deploying it in a field study. If time permitted, we asked participants as a final task, to first define a task on their own, and secondly, to solve it using F3.

#	Description	# of necessary interactions and difficulty
1	How many patients were admitted to Herlev hospital?	2 (brief)
2	How many 11 year olds were admitted?	2 (brief)
3	What was the average age of patients admitted in the capital region?	2 (brief)
4	How many patient were admitted in relation to labor and birth in total?	2 (brief)
5	How many patients at 65 and older received plastic surgery at Odense University hospital (OUH)?	6 (long)
6	Which age groups gave birth by Caesarean section in 2013?	6 (long)
7	Which hospitals had a high increase of plastic surgeries from 2012 to 2013?	~10 (complex)
8	Which treatments types are cheaper on large hospitals than small hospitals in the capital region?	~10 (complex)
9	First, define a task on your own. Next, try to solve it.	varied (complex)

Table 6.3: Tasks for the formative study (study 1).

6.4.2 Procedure

During the sessions, a facilitator and an observer were present in the room, besides a participant. The facilitator's role was to keep the sessions on track and the participants at ease. The observer's role was to observe and take notes. Both were allowed to ask questions.

First, we introduced participants to the study and its goals. They gave consent to participate, and filled in a background questionnaire.

Then, we asked participants to use the system, and to explore the interaction techniques. To assure participants understood and used the entire range of interaction techniques, we observed them closely in this phase and gave suggestions about what to try if they were in doubt. We encouraged participants to ask questions throughout the session.

After we introduced participants to F3, we asked them to work with the tasks described above, one by one. We administered the tasks in writing. After each task, we asked the participants if they had any questions. If time permitted, the facilitator and observer asked questions, before moving onto the next task.

At the end of the session, we interviewed participants about their experience with the system and interactions, including its benefits and drawbacks compared to other systems they knew, and followed up on aspects of their interactions or what they said during the session.

The sessions lasted between 55 and 65 minutes.

6.4.3 Data Collection and Analysis

Participants were video recorded, and the facilitator and observer kept notes of usability issues and participants' utterances. We also used the notes as basis for the interview described above.

We analysed the collected data in four analysis sessions based on the Instant Data Analysis technique [84]. The analysis sessions, which we conducted within a day after participant sessions, lasted on average one hour. For the analysis, we gathered in front of a whiteboard. We transferred observations to sticky notes, fixed them to a whiteboard, and presented and discussed our observations. We then categorized the sticky notes into themes and clustered them on the whiteboard. Based on the clusters, we captured the most important findings with references to the observations and any supporting video recordings.

6.4.4 Results

First, I describe which techniques participants used. Then I present the results in terms of five topics that we observed across several participants.

Use of F3's Interaction Techniques

All nine participants understood and used view creation, configuration, cloning, and exploration. Many participants seemed uncertain about the effects of the other techniques, both before and after we guided them through using the techniques. Only one participant actively used view matrix creation and no one used trail cloning.

One participant quickly understood how view cloning would enable him to try out new approaches and strategies, which enabled him to perform a range of analyses in a rapid manner.

Drilling Too Deep

Seven out of nine participants *drilled too deep* (depicted in Figure 6.12). While reading off the value of a data bar might solve a task, participants instead dragged the data bar out of the view, thus creating a new view drilled down in the aggregate. This did not give them the answer to the task. Some participants merely stopped looking at or explicitly closed the child view, and read it from the parent view as required, while other participants got confused and either stopped to consider what to do, or alternatively, tried to manually aggregate data in the child view.

Participants found F3 backwards when they wanted to isolate a member from one view in another view, aggregated by another dimension. F3 lets users do that by dragging out the data bar, (i.e., drilling), and then configuring the view with the needed dimension. For example, if participants needed to see a view filtered on a single hospital, they often created of view of hospitals, and then dragged out the wanted hospital. This resulted in a drill-down on hospital, thus creating a view of wards on the chosen hospital. To see other aspects of the hospital, participants had to drag another dimension onto the x-axis, which they seemed to either not remember or understand.

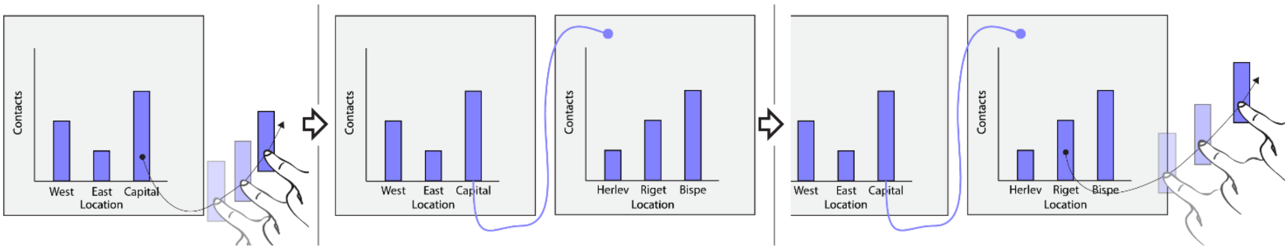


Figure 6.12. Many participants *drilled too deep*. This figure shows an example of this. For example, if we asked participants to find the amount of patient contacts at the hospital “Riget”, they drilled further into the “Riget” data bar than necessary. This led to a view that showed the wards at “Riget” and thus confused participants, because they reached a level of detail higher than necessary, and could neither read the result or continue interacting in a sensible manner.

Combinations of User Interface Parts

Some participants were unsure about possible combinations of user interface parts. They had understood that it was possible to combine many elements, but it was unclear to participants, which particular elements that it was possible to combine. Consequently, participants tried to combine elements in ways that we had neither considered nor implemented. One participant, for example, tried to drag two data bars together, which F3 does not support. When we asked the participant what she expected the result of the action to be, she suggested that it might show both data bars in a view. Two participants also tried to drag a view to another views’ explode area, which they seemed to expect to result in exploding the view by data bars in the dragged view.

It seemed that some participants did not consider what they were dragging, but only where they dropped it. For example, a participant dragged a data bar over many parts of the user interface while thinking, reminding of Dwyer et al.’s “thinking with their hands” [38].

Default Axes

Default axis selection seemed to create some confusion when participants had created views. It seemed they were not aware of the default choice, but only realized it when they needed to solve a task that required them to select another measure.

Data Exploration

Two participants suggested that F3 would be a good tool for exploring data. A participant that had obtained a particularly good grasp of the different possibilities considered two ways a data exploration could progress: He could create consecutive child views by drilling and reconfiguring, for example to see data for people above 65 that had plastic surgery performed at a specific hospital. This would leave a trail of the exploration process. Alternatively, he suggested creating three views that showed age groups, treatment types, and hospitals. He would then drill on one of these views, and later filter the resulting view using the other views. The result would be identical, but the process of getting there, and the layout and relations between views, would be radically different.

In contrast to this, a participant said that she was used to seeing more information in a single view. She thought it weird with so little information in each view, but so many views. In addition, this participant suggested that the system was too visual, and that she would rather conduct her analyses by programming and looking at data tables. This repeats findings by Kandel et al. [82].

Experience

Many participants found F3 useful and efficient, in spite of their confusion. Two participants said that F3 provided playful interactions. In the debriefing, they considered how they would analyse their own data with F3. One participant described F3 as "*simple charts, fast*". Another participant emphasized the speed at which she was able to conduct analyses with F3. On her way out the door, one participant said "*bye, bye. It was fun to play…*", which stressed the experience that she had had with the system. In contrast, a participant that had many problems using F3 said he "*lacked the appetite*" for using it.

6.4.5 Summary

Participants in the lab study used all of the interaction techniques, except for *trail cloning* and *view matrix creation*. We expected that part of the reason that no participants used two of the techniques were that they did not have enough time with the system, and that the tasks we asked them to solve, were so simple that using them was unnecessary. An alternative explanation is that they were too complex. We expected the second study to shed more light on this.

The issue of *drilling too deep* occurred in almost all lab sessions. It is evident that some aspect of F3 caused participants to *drill too deep*. However, we were in doubt about the reason for participants' behaviour, and were curious to find whether the second study could provide further explanations.

It was also clear from the study that many participants formed a mental model of the possibilities for dropping data bars on views, which were different from what we intended with F3's design. It was encouraging that participants acquired the conceptual drag and drop model, but clear that they understood it slightly different and that F3's feedback needs improvement.

Finally, many participants emphasized the explorative approach to data analysis provided by F3's, and described the experience of using it as fun or fast.

Next, I describe a field study of F3, which shed further light on some of the described issues.

6.5 Study #2: Field Study

Where the first study sought to evaluate the usability of the interaction techniques, the second study focused on how the health care analysts described in section 6.1.1 would use the interaction techniques as an integral part of their work. The study aimed to understand how F3 support data analysis tasks that span hours or perhaps days and that involve data exploration. We based the study on real data and tasks that potentially involved many analysts. The duration of this study allowed us to understand the benefits of one interaction technique over another, and to understand how analysts can use F3's interaction techniques creatively to explore data, uncover new understanding, and gain insight.

The seventh to ninth row (deployment study) in Table 6.1 shows this work.

6.5.1 Deployment

We deployed the 84" display and F3 in the offices where the analysts worked during two regular workweeks. Initially, we installed the display in an office shared by two employees and an external consultant (first location). Few employees used the display in that location. We believe that the location seemed too personal to employees that did not work in the office, and did not allow people to step back from the display to gain overview. Therefore, after four workdays, we moved the display to a small room that employees regularly used for impromptu stand-up meetings and that more people passed during their workday (second location). Aside from the display, there were two tall café tables in the room. In this location, a more varied group of people used F3. Moving the display created new interest, even from those had been sitting near the first location. The display remained in this location for the remaining six workdays. During the entire period, we expect that about twenty people have interacted with the system. The seventh and eighth row (deployment study) in Table 6.1 shows twenty participant squares. Three of these are dark grey and three black. These six analysts used the system for more than half of the time. The three black squares represent participants that we interviewed on the last day of the deployment. In total, 907 views were created comprising all F3's techniques.

6.5.2 Data Collection

To obtain a satisfying understanding of how the analysts used the display during the deployment, we based data collection on triangulation: We logged user interactions, captured screenshots at 5-second intervals, and recorded audio during system use. In addition, we visited the deployment site at least once every day for one to six hours to make sure the system was being used, to observe the use, to conduct interviews, and to resolve technical problems. We kept field notes while on-site. Immediately after leaving the site, we logged short audio memos to describe our observations from the visit. Our inquiries with the group of analysts over the past three years provided further context to understand F3's use in the broader context of their work. In addition, we used the visits to gather requests for features or updates to the data model. These requests were actively encouraged, to create pull from the analysts. Finally, we conducted interviews with three key analysts at the end of the deployment period (see Table 6.1).

6.5.3 Making Sense of the Collected Data

Analysis was informed by Grounded Theory [139]. Carpendale [26] and Isenberg et al. [71] advocated for using Grounded Theory to analyse qualitative study data in InfoVis. We continuously moved from the field to the data and back again, reformulating our coding and questions, thereby gaining understanding of the way the analysts used F3. The collection and analysis of data also served to address deployment issues.

At the end of the deployment, we gathered all data to obtain an overview: We transcribed observation audio memos, and along with notes from interviews and observations transferred these to sticky notes to facilitate affinity diagramming.. We used the sticky notes as entry points for further analyses of screenshots and audio recordings to provide additional detail when necessary. Some notes specifically suggested returning to the audio material to obtain greater insight, which resulted in adding new data to the affinity diagram. We only used interaction logs to describe the extent of F3's use during the deployment, because the logs contained noise caused by our presence at the site of deployment. For example, we caused noise by suggesting analysts which interaction techniques to try and by our own interactions with the system. The final part of analysis condensed seven themes, which I describe next.

6.5.4 Field Study Results

I present the results in terms of seven themes.

Use of Display Space

The health care analysts used the entire display to lay out views, although they first and most used the left-centre area. The analysts never positioned views such that they extended towards the top border. A few views extended the left or right border, such that most of the view remained visible. On one occasion, the analysts positioned views extending below the display, to store unused views.

Interaction Techniques and Data Model

During the two weeks of deployment, the analysts used all of F3's interaction techniques, except for *trail cloning* and *view matrix creation* (similar to the lab study).

The analysts requested many additional features from F3 during the deployment. We logged feature requests, but chose not to provide any of them, which would potentially alter the system dramatically. The most common requests were to provide view scaling to show more data bars in a view and provide additional visualization techniques (e.g., scatterplots). The analysts also frequently asked for general process and provenance [61] support in F3 (e.g., annotate, record, share, desktop integration). More rare requests centred on the visualization and interaction techniques provided by

F3. The analysts wanted visualizations to: show several measures in bar charts next to each other; to allow analytical abstractions (e.g., show the difference of two views); and to show stacked bar charts. The analysts asked for interaction that focused on views. For example, to be able to undo actions, drill-up and down, and filter, all within a single view. Aside from within-view interactions, the analysts wanted to be able to create a new view with a single data member (i.e., a filter) by dropping a dragged data bar on the canvas similar to view exploration, but without drilling, to be able to select a few aggregates to continue exploring. This shows that what normally was an effective technique, seemed to limit participants in some circumstances. An analyst described the difficulty in removing a single member from a view. We designed F3 to show all filters explicitly through view relations. We therefore chose not to provide a simple technique for this. Instead, users can use view exploration, followed by inverting the relation. Although this solution is more complicated than what the analysts asked for, it helps to understand the filters applied to data.

The analysts requested many updates to the data model. For example, we added 14 new dimensions, thus resulting in 21 dimensions at the end of the deployment period. These requests illustrate the analysts' motivation for using the system – they were eager to use F3, and to use it for more than they could without updates to the data model.

The analysts also requested updates to the data model that we chose not to provide. Particularly, the analysts asked to derive a new dimension from two existing. We showed them that they would be able to use F3 to combine aggregates from the two dimensions to obtain a similar combination, and thus opted to let them explore this possibility instead. From this, they were able to identify errors in data received from a specific region.

Exploration of Data

Quick insights: After an analyst had discovered what seemed to be an important data error in a matter of seconds with F3, he estimated that it would take 30 minutes to conduct a similar exploration with their current practice. When asked to compare the current analysis practice to using F3, he said *"[F3] is more playful, the leap from thought to action and result is shorter"*, and that "*there are fewer steps involved"*. When F3 crashed (which it did on occasion), he said that he *"was forced to remember what he had done"* which showed that, although the fast and fluid properties had helped him to perform analyses quickly, remembering what he had done was difficult. F3 would have helped him in this regard by showing views' relations, but when it crashed, it clearly demonstrated the support given by showing those relations. This shows that he used F3, without thinking consciously about how he approached the exploration. He also stated that, *"our current practice also leaves more flexibility [in terms of how we can perform analyses]"*. Another analyst described working with F3 as *"impromptu analyses in data"*. She described F3 as quick to provide results, as visual (as opposed to looking at tables in SAS), and as flexible, in that dimensions and measures can be the combined simply by drag and drop.

Problematically playful: The playful quality was problematic in some circumstances. In some analyses, it was clear that analysts were too fast, without keeping their goal in mind, and drilled too deep (as in study #1) into a slice of the data set. It seems that keeping a mental overview, while playing and exploring the data was problematic for the analysts. One analyst thought that it was *"a bit harder to keep the overview, because it is so easy to drag something new in, whereas if we are programming it, we typically plan what we want to do beforehand. Here, you typically drag something to see: how does that look? Is it something to proceed with, and otherwise you close and continue"*.

Difference to current practice: The analysts described the difference between their current practice and using F3 in terms of how they find errors in data: *"You don't sit and play with the data. Most often, you're looking for something specific."* This showed that the fast and fluid properties of F3 provided the analysts with new possibilities for exploring data, and find anomalies or errors, that they were unable to find easily otherwise. Another analyst further commented that seeing the context of a task with more data was useful, and increased her awareness of the task. The analysts liked how F3 helped constructing new hypotheses in their analysis by supporting exploration of data. One analyst said: "*[F3] is good for getting ideas. Ideas that should be looked into"*. Here, ideas covered data errors and other things that the analysts would like to correct.

We attributed the playfulness of F3 to the fact that it is easy to experiment, create new views ad hoc, and possibly close them again if necessary. In short, getting from idea to action is fast, and any action is easily reversible, which both promotes experimenting and playing.

Visualizations of Data and Relations

The analysts liked that F3 showed data visually, but also commented that they were not used to see data that way (the analysts primarily use data table representations when looking at data). An analyst said that she had to *"get used to seeing data visually"* – which she described was hard for her. At least five analysts repeated this sentiment in various forms. They did see the value in the visualizations, but some also used the textual representations of aggregate values that F3 showed when tapping a data bar. This seemed to reduce misreading visualizations, for example by facilitating a sanity check for scaling similarity in compared views.

The analysts liked the way that F3 visualizes the relations between views. One analyst for example said: *"I can obtain an overview of how the views are created"*. We suspected that these representations helped participants understand F3's feedback during interaction, but have no empirical evidence for this.

Views as Toolboxes

In F3, we noticed that some participants used views as tools. I call these *toolbox views*. They are views that users create, only to be able to drag data from the views to filter other views, which have the users' focus. Toolbox views bring little value except for helping other exploration steps. The ability to use toolbox views in F3 is unique, in that auxiliary views make use of the abundant display space. With less display space, using toolbox views would seem like wasting pixels.

An analyst that was quick to grasp the idea of using views as tools said: *"You just have to turn it up-side down in your mind"*. Most of the other analysts seemed to find it difficult to use views as a tool in exploration, and seemed to forget the approach. However, as one analyst said: *"If you are looking into a specific problem, seeing the context is important"*. In this statement, the context was a view, and the object of interest a data bar dragged from the view.

Collaboration

The analysts considered using F3 in collaborations with peers on-site. They experienced such collaborations during the deployment and thus considered how F3 could become a permanent part of their work. For example, an analyst said that using the display during analysis meetings would facilitate answering of open questions straight away during meetings, supported by F3's simple and fast interactions. In contrast, current analysis meeting practice is to present data and analysis problems, note questions and comments, and return to their desk after the meeting to continue their analysis based on the received questions and comments, as outlined in section 2.1. This suggests F3's value in internal collaboration. The analysts also described how F3 invited for discussions about data. One analyst said that collaboration between several analysts helped generate analyses and ideas, and that it was easier, more fun, and less error prone than doing it alone.

The analysts also frequently considered using F3 for communications with external collaborators such as clinical societies, policy makers, and regional healthcare professionals. For example, when two analysts showed F3 to a group of collaborators from a university hospital, they collaboratively discovered a data error. An analyst suggested that F3 could improve the process of collaborating with clinical societies. She imagined that instead of endless series of meetings and email exchanges that take the form of negotiations, using F3 could facilitate collaboration, increase mutual understanding of complex issues, and help to arrive at conclusions faster.

The Health Care Analysts Obtained New Insights

During the study, the analysts found three potential data errors, which they added to a list of concerns. According to the analysts, this was much more than expected. For example, they discovered that the average amount of bed days for a region was four times higher than other regions. They hypothesized that the region had conducted incorrect registrations, conducted registrations according to an old standard, or that an internal process had failed to remove parts of data that were irrelevant for later analysis. We inquired if and how finding the potential data problems was due to F3. The reasons most often attributed to finding errors, was the speed of data exploration with F3, and that they could collaborate efficiently in the process.

6.6 Discussion

I have presented F3, a system that implements a selection of interaction techniques that (a) use touch to create and combine visualizations and (b) work well with abundant display space. Next, I discuss the interaction techniques in F3, the two complementary empirical studies of F3, and limitations/future work.

6.6.1 Benefits of Interaction Techniques in F3

In designing F3, we wanted to enable users to touch, drag and drop as many visualization elements and data fields in the user interface as possible. Participants liked being able to drag things out of views and generate new views. Our studies suggest that this could be due to the direct mapping between what they saw, what they did, the reaction they obtained, and how F3 represented this visually with links. I believe this a key strength of the interaction techniques used F3. However, we also observed some participants' uncertainties about component mappings in study #1, which later inquiry confirmed. There are two takeaways from this: First, participants formed conceptual models of where data fields and aggregates could be dropped, and assumed that other parts of the interface worked similarly. A guessability study might provide the necessary information about the additional possibilities for a redesign. Second, the feedback provided by F3 should be improved to give more clear information of where data fields and aggregates could be dropped.

I believe F3 allows users to create many views easily, thereby making use of the abundant display space. While this follows suggestions from earlier work (e.g., Paper I described in Chapter 4), I argue that several of the interaction techniques in F3 are novel in this regard. The empirical work suggests that some of the interaction techniques (e.g., view cloning, exploration, filtering, and exploding) were easy to understand and useful. These techniques helped participants think and execute complex data explorations quickly, some of which took hours of trial-and-error in their current system. While some of these would have benefitted from any kind of visualization, I believe that the aggressive creation and expansion of visualizations in F3 is the key benefit.

6.6.2 Too Fast, Fluid, and Flexible?

Our empirical results have shown that participants in both studies were able to perform fast analyses and combine different attributes, supported by F3's interaction techniques. However, some results also indicated problems. I speculate if our design goals partly caused the observed problems, and whether such effects can be observed with other systems.

Participants' confusion about automatic selections in the first study is a direct result of our design choice. We deliberately opted to prepopulate undefined axes to present data as fast as possible. Participants also drilled too deep. Could the focus on fluidity and never-ending interactions cause users to keep interacting, instead of reading the obtained result?

Participants' uncertainty about how to proceed with a complex data exploration in the first study might result from our design choices. The order in which users can perform data exploration operations with F3 provides flexibility (e.g., toolbox views). However, this flexibility might also cause inexperienced users more uncertainty and confusion. We had designed for this flexibility, but observed that some novice users had difficulties planning and executing analyses, potentially due to these choices.

6.6.3 Empirical Studies of F3

The results of the studies suggest that users were able to use the techniques to perform data exploration and found them useful. I can think of only few studies showing such findings in a field study.

The laboratory study identified concerns such as too much drilling, which largely were unimportant in the second study. One reason for this was that the analysts in the second study had much longer time to learn to use F3, and to apply the techniques to perform data exploration as part of solving their analysis tasks.

I want to discuss briefly our choice of methods. Empirical work is scarce in the related work. At least a part of this reason is that large touch displays has only recently become available. Another reason for the lack of empirical work is that it is difficult to establish good collaborations with experts that are motivated to use research prototypes. In addition, information visualization research has only in the last decade begun to use empirical studies as a crucial evaluation method [72, 88].

I acknowledge that it is difficult to separate the effects of the specific system (F3) from the general technology (large display visualizations) in field studies such as the reported. However, I believe that the field study showed that F3 enables collaborative data exploration in a manner and efficiency that other systems do not support. For example shown by the fact that external collaborators were able to take part in exploring data with F3.

6.6.4 Limitations

F3 is limited by supporting only bar charts; we prioritized instead to make it work with large-scale data that could be used in a field setting. Support for alternative views was a common request from participants in both studies. Many of the interaction techniques can easily be applied to other visualization techniques, for which there are plentiful [59]. Selections in scatterplots may also be designed such that they facilitate dragging them out of a view, to isolate in another (e.g., like selections in [122]). Some of the interaction techniques may well be more useful with other visual representations. For example, other work has shown that scatterplot matrices are extremely valuable for some tasks, and thus matrix view creation may thus be more effective with scatterplots.

6.7 Summary and conclusion

In designing, implementing and evaluating F3 and the interaction techniques that it is based on, we showed the value of combining information visualization, large displays, and touch interaction, to support collaborative data exploration.

The field study showed analysts' ability to use F3 to perform exploratory data analysis, and obtain insights more quickly than they were accustomed to with their current tools and systems.

Many issues are still open, many questions unanswered, and more research needed. Specifically, the discussion above have outlined questions that we cannot answer from the evaluations we conducted. Specifically, I speculate if we might have taken our focus on providing fast, fluid, and flexible interaction techniques in designing F3 too far.

As part of designing F3, we became aware of the importance of showing views' relations. In F3, we showed this using links between data bars and filter dots. This awareness led to considering other visualization techniques for showing relations between views. In the next paper, we explored the possibilities for showing relations between views more generally.

Chapter 7

Paper IV

Representing View Relations: A Qualitative Study on Between-View Meta-Visualizations

S. Knudsen & S. Carpendale

Abstract – To improve our understanding of the use of meta-visualizations to help explain view relations, we conducted a qualitative study in which we invited people with experience in both visualization and interaction design to work with, discuss and sketch representations of view relations. Because data analysis based on visualizations frequently involves creating and navigating many visualization views, it is becoming important to develop ways to keep track of how one visualization view relates to another. The pressure to find effective solutions for representing the relations between views is being fuelled by the increasing prevalence of large, high-resolution displays, which provide more space for multiple views and view organization. However, the simple increase in display size does not inherently provide the additional analysis support that may be needed. Between-view meta-visualizations may help to address this need by offering methods that can reveal relations between views. Through our exploration of the possibilities for showing between-view relations, we discovered several factors such as the data itself, the parts of the data that are shown, the flow of data, the encoding of data, the view coordination, and the interactions that can be used as part of meta-visualization representations. Our results, together with existing research, form the basis of a six dimensional framework that expands the range of possibilities of between-view meta-visualizations.

My contributions to Paper IV

I identified the research problem of understanding relations between views based on insights from a study I conducted on a basic version F3 (see Table 6.1, rows 4 and 5), which I described in the previous chapter. Professor Sheelagh Carpendale contributed revisions to the problem and study design.

I carried the main responsibility of data collection by implementing the design scenes, running the study sessions, and subsequently analysing the collected data, all of which are described in the following. Professor Sheelagh Carpendale contributed to data analysis through verbal and textual discussions.

I wrote the first draft of the paper and drew all figures. Both Professor Sheelagh Carpendale and I contributed with subsequent revisions to the draft.

In the fourth paper, we wanted to explore potential relations between visualization views and the possibilities of representing these.

I was specifically inspired by:

1. The way, in which participants in the study described in Paper I had shown visualizations' relations with trails of thought (see Chapter 4).
2. The process of designing and evaluating F3 in Paper III (see previous chapter). Specifically, the issues I observed in the small informal lab study of F3 (see Table 6.1, rows 4 and 5) and the eventual design choices for F3.
3. My collaborator's previous studies [29, 143] and other related work (e.g., [37, 80, 79, 130, 151, 158]).

The aim of our work was to improve our understanding of view relations, and their possible representations. These require definitions:

A *View* is a bounded area that has its own use of spatial organization that displays any variations of datasets and their representations. View boundaries may be represented visually using borders, backgrounds, or similar techniques.

A *View relation* is a property shared by two views, which for example include data, the way the views show data, or the way users created the views.

A *Representation of a view relation* is a meta-view visualization that indicate a view relation. Thus, such representations often cross views' boundaries, or use visual variables to show views' relations on top of views.

To improve our understanding of view relations, and their possible representations, we conducted a qualitative study in which we invited people with considerable experience in both visualization and interaction design to work with, discuss and sketch representations of view relations. Rather than designing, implementing, and testing one single possible design (as I had done in the work of F3, which I described in Chapter 6), we chose to study the range of possible meta-view visualizations. The aim was to expand our understanding of meta-visualizations in visualization and interaction design. To do this, we developed many alternative designs, and implemented them as low fidelity prototypes. The prototypes allowed us to present several ideas to participants and run a review of these designs. We were interested in the participants' interpretation of the relations represented in the designs, which relations they found sensible and useful, and other designs they might imagine. This allowed us to gain knowledge of the strengths and weaknesses of the view relations and their representations.

7.1 Methodology

We conducted 10 sessions that lasted approximately 1½ hours and consisted of three phases: Briefing, design review, and de-briefing. The first and last phases merely set the frame for the design review, which I describe briefly in the following.

In the design review, participants worked with seven scene designs on an 84” pen and touch display [169]. The scenes consisted of visualization views and between-view relation representations. Some scenes captured ideas from related work, while others were novel. Scene 1 and 5 were inspired by GraphTrail [37], scene 2 by VisLink [29], scene 3 by DragMag [158], and scene 4 by Lark [143]. In contrast, scene 6 was based on the idea of considering legends in relation representations, and scene 7 on the idea of showing meta-data in separate views. Figures 7.20 to 7.26 show screenshots of the seven scenes. We did not intend to produce faithful reproductions of the related work, but rather aimed to use the scenes as conversation catalysts. The goal of offering many alternatives was to allow participants to compare ideas and to provide variability to the study [144], thus inspiring participants to come up with their own ideas.

The design review consisted of two parts: A and B. In both parts, participants worked with the seven scenes. During part A, participants reviewed our relation designs. During part B, we only showed participants the views, and asked them to come up with their own relation representations. To identify study bias, we chose to divide the participants’ sessions in two: we conducted half of the sessions in AB order, and the other half in BA order.

We recorded audio and video of the sessions. We also recorded screen captures in five-second intervals to collect participants’ sketches. After conducting the sessions, we analysed the recorded material based on a grounded theory approach [71, 139]. Although we initiated the study with some ideas of what to look for (based on related work [29, 37, 80, 79, 130, 143, 151, 158]), we also looked for new ideas and concepts while analysing the gathered data. As part of analysing the data, we used open coding, from which we developed a set of thirteen concepts. These concepts worked well to convey the range of thoughts and ideas that participants expressed. We used these concepts as a basis, combined with related work, to assemble a framework composed of six different dimensions of view relations. We did this to provide concrete, practical suggestions of what to consider, from the perspective of designing and evaluating concrete meta-view relation representations. Whereas many of the concepts concerned the visual properties of meta-representations that participants considered, the dimensions consider properties of the *views’ relations* in themselves, which designers may choose to show with different visual properties or techniques.

Table 7.1 provides an overview of the methods used in the study. Next, I provide an overview of the findings in terms of the framework.

Paper	Aim	Method	Collected data	Analysis	Medium	Participants
IV	Explore and evaluate view relation representations	Expert evaluation and design (sketching)	70 sketches 15 hours of video	Grounded Theory	Large touch and pen display	Visualization experts

Table 7.1: Overview of study methods.

7.2 Framework and Findings

The framework consists of six dimensions of view relations and their representations: design intent, visual components, re-use of view representations, direction, strength, and interference with views. Figure 7.19 shows the dimensions and depict related work in terms of the framework. I describe each framework dimension in the following.

7.2.1 Design intent

Design intent considers what the purpose is of showing a relation representation and relates to how designers aim to support data analysis. *Design intent* describes the designers' perspective. Thus, a design may be useful for other purposes than what the focus of the design was, and a single design may cover more than a single *design intent*. We used the word intent because intent captures a design's idea, rather than what it enables. In the following, I describe five *design intents* of showing relations:

Data relations intend to show the relation between data present in two views, conveying which data is affected using different visualization techniques, choices of encoding, or data processing. Examples of showing data relations include using colour similarly in two views and linking data points across views (e.g., [29, 130, 151]). Figure 7.1 shows an example of representing data relations.

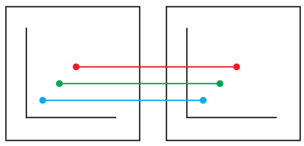


Figure 7.1. Showing data relations. The two views show the same data points. The line connections show this relation.

Process relations intend to show how data has been processed or transformed between two views, e.g., through filtering, aggregating, deriving, or any other process. Lark [143] and ExPlates [80] showed processing explicitly with lines connected to views. GraphTrail [37] used line connections, but was not explicit in how data had been processed between views. Figure 7.2 shows an example of representing process relations.

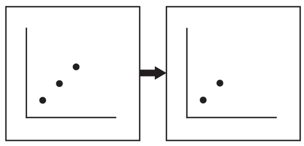


Figure 7.2. Showing process relations. The view on the right is a filtered version of the left, which is indicated by the line arrow.

Encoding relations intend to show the data encoding differences or similarities between two views, e.g., by using highlighting or connecting axes, or connecting legends. In Lark [143], views' encoding relations were shown explicitly through the InfoVis pipeline representation. Figure 7.3 shows an example of representing encoding relations.

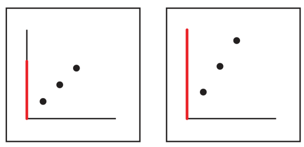


Figure 7.3. Showing encoding relations. The views' y-axes encode the same attribute with different scale. The red highlighting shows this.

Interaction relations intend to show how views relate based on people's interaction with views, e.g., by having used one view to create another or by whom created or positioned a view. GraphTrail [37] and ExPlates [80] used interaction relations to show analysis history. Lark [143] also showed interaction relations. Here, the intention with was to support collaboration. Figure 7.4 shows an example of representing interaction relations.

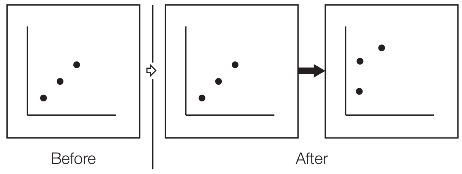


Figure 7.4. Showing interaction. The view to the right was created from the other view. This is shown with the thick line connection.

Coordination relations intend to show how views are coordinated, e.g., by brushing and linking techniques. I am not aware of any work that shows coordination relations explicitly, but Lark shows coordination implicitly through the visualization pipeline [143]. A participant in our study suggested these relations might be experienced through interaction (e.g., brushing). In Paper IV, we suggested that showing coordination relations explicitly might be useful in contexts where many people use many views. Figure 7.5 shows an example of representing coordination relations.

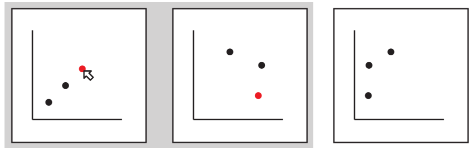
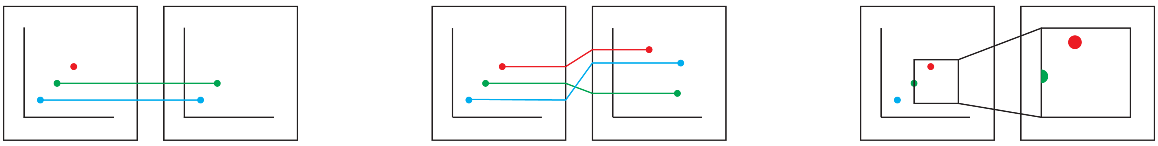


Figure 7.5. Showing coordination relations. Views to the left are coordinated, shown by the grey area.

Intent can be multi-faceted: a relation representation that shows data relations may also show process. For example, if a view shows a subset of data points from another view and the data points are connected, then the relation shows both data *and* process. Figure 7.6 shows this example as well as other multi-faceted relation representations.



(a) Data and process (b) Data and encoding (c) Encoding and process

Fig. 7.6. Examples of multiple design intents. (a) and (b): intent to show data relations in that the meta-visualization shows the location of data points in both views. (a) and (c): intent to show process in that the meta-visualization indicates a relation between a subset of data. (b) and (c): intent to show encoding relations, in that meta-visualization shows relations between the views' encoding (the axes).

The dimension arose from the analysis of the study data. The data showed participants' varied considerations about tasks that view relation representations support. This supports the choice of considering design intent as part of the framework. One participant for example considered: *"if you want to follow a specific country, then this relation, in that case is more important. It completely depends on the context"*. Other concepts that emerged from our analysis supported the division of design intent. For example, we identified *axis relation*, *legend relation*, and *interaction* concepts. We mapped the first two concepts to encoding and the last concept to the interaction and coordination design intents.

7.2.2 Visual components

Visual components delineate the different components that designers can use in showing view relations. We ordered these in a three-level hierarchy:

Data components comprise visual marks that represent data: points in scatterplots, bars in bar charts or rectangles in treemaps. VisLink [29] showed relations between data components. Figure 7.7 shows an example of showing relations between data components.

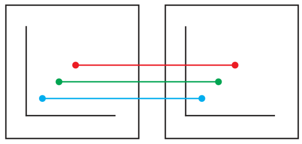


Figure 7.7. Showing data to data relations.

Meta-data components comprise factors included in the visualization to help with readability such as axes, legends, and grid lines. For example, Classen & Wijk [28] showed relations between views' axes (meta-data components). Figure 7.8 shows an example of showing relations between meta-data components.

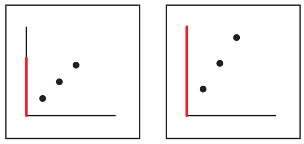


Figure 7.8. Showing meta-data to meta-data relations.

View components comprise factors that contain and separate the view from the rest of the display such as view borders, corners, background, and title. ExPlates [80] showed line connections between views' borders. Figure 7.9 shows an example of showing relations between view components.

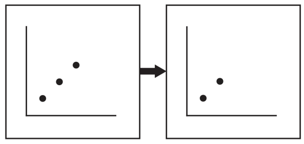
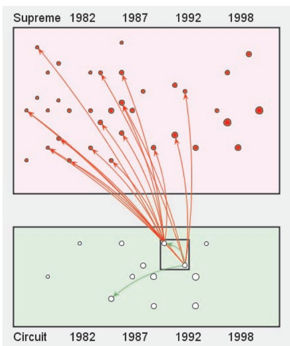
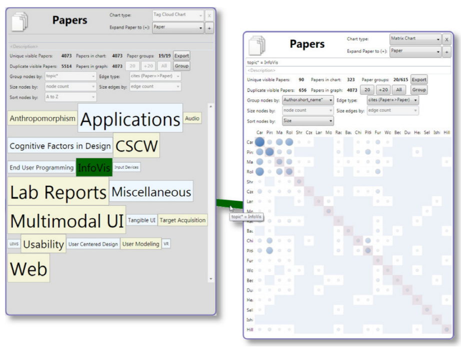


Figure 7.9. Showing view to view relations.

Different component levels might be involved in showing relations between two views. For example: Semantic Substrates [130] showed relations between a data points (data components) in a rectangle (meta-data component) that referred to axes in a view, to data points (data components) in another view. GraphTrail [37] showed line connections between views' borders (view components), while the colour of the line mapped the selected data in views (data components). Figure 7.10 shows these examples.



Semantic Substrates [130]

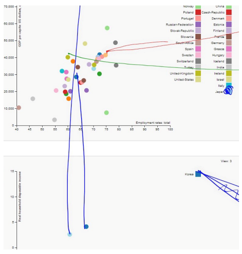


GraphTrail [37]

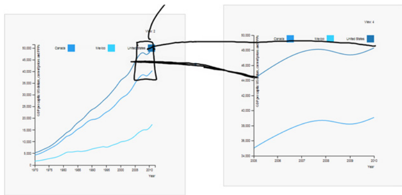
Figure 7.10. Literature examples of using different components to show views' relations.

The dimension arose from the analysis of the study data. The data showed the study participants' varied uses of visual components to show view relations. Figure 7.11 shows examples of these variations. For example, in Figure 7.11c, a participant considered how to show an overview plus detail relation between two line plots, and suggested to connect the line start and end points in the detail view.

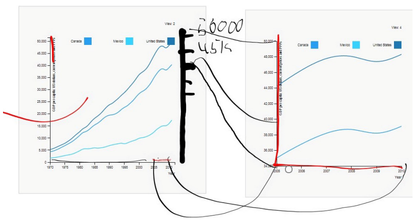
a: 1 (3)
Data and meta-data components



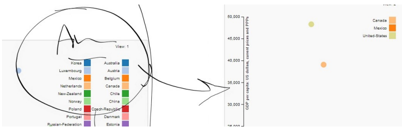
b: 2 (5)
Data components



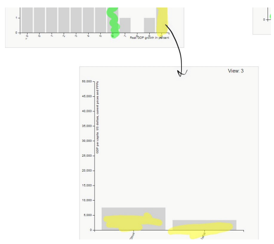
c: 3 (0)
Data components



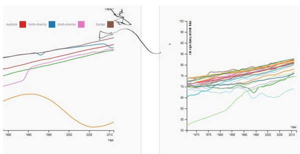
d: 3 (2)
Meta-data components



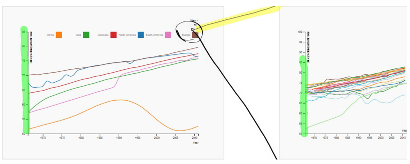
e: 4 (8)
Meta-data and view components



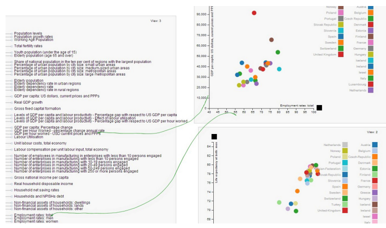
f: 5 (8)
Data and view components



g: 6 (7)
Data and view components



h: 6 (8)
Meta-data and view components



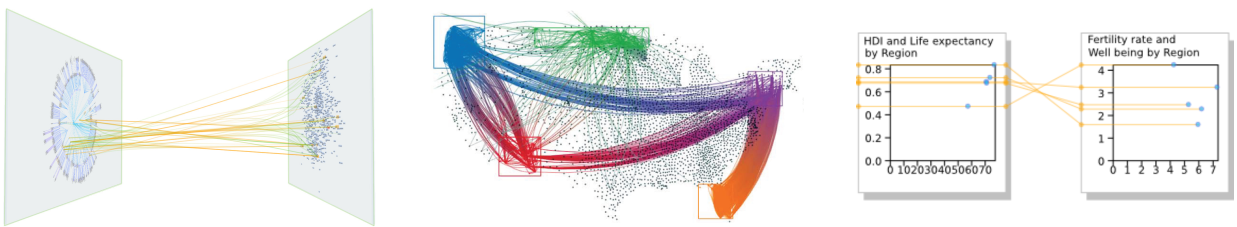
i: 7 (2)
Data and meta-data components

Figure 7.11. Participants' sketches showed varied uses of visual components to represent view relations. The text below each subfigure indicates the occurrence of sketches as "subfigure: scene (participant)".

7.2.3 Re-use of view representations

Re-use of view representations captures how designers may use data encodings within views in relation representations. For example, a line connection between two views can use the views' internal colour encoding to colour the lines. Similarly, a bar in a bar chart may be divided into a stacked bar, thereby using the spatial layout of the bar chart to make it easier to understand a relation to another view.

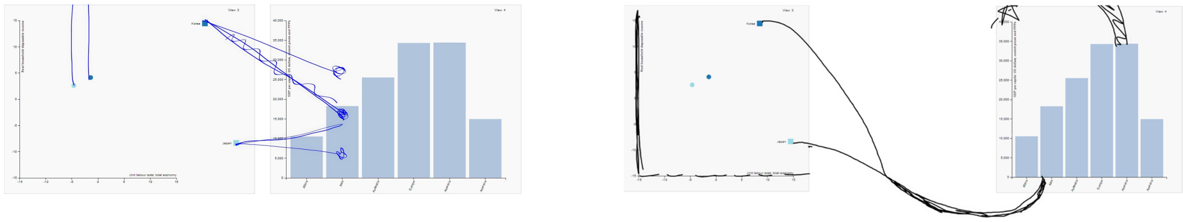
We denote relation representations that re-use views' representations as consistent with the views' visual encodings. Lines coloured similar to the data points they connect are consistent with the views' visual encodings. Likewise, we denote relation representations that use the views' visual encodings to convey separate information as inconsistent. Lines representing view to view relations that are coloured similar to data points in the views are inconsistent. While we are not aware of work that focuses on re-use of view representations, some systems use the idea. For example, VisLink [29] and Elzen & Wijk [41] used colours within views to colour lines between views, while ConnectedCharts [151] used the position of data points to anchor relation lines to axes and chart edges. Figure 7.12 shows these examples.



VisLink [29] Elzen & Wijk [41] ConnectedCharts [151]

Figure 7.12. Literature examples that re-use visual encodings within views' to show relations between views.

In contrast to the rare consideration of this dimension in related work, the study participants frequently considered re-using within-view representations. For example, participants re-used colours of linked data points for colouring the links (see Figure 7.11b), connected data points in one view to positions within data bars in another view (see Figure 7.13a), and used line end points to encode specific data values on vertical axes in both views (see Figure 7.11c). Additionally, they merged lines from multiple legend items and connected these to data bars in other views. This allowed line thickness to represent the fraction of the data bar indicated (see Figure 7.13.b) to *"encode more information"*.



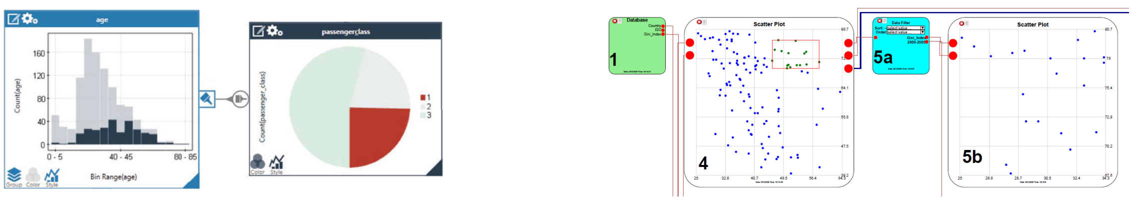
a: 2 (5)

b: 2 (0)

Fig. 7.13. Examples of participants' re-use of within-view representations. The text below each subfigure indicates the occurrence of sketches as "subfigure: scene (participant)".

7.2.4 Direction

Direction of relations captures that view relations can be can be directed or undirected. If source and destination views exist, the meta-view representation may show this. For example, an arrowed line may connect a source view to a destination view [167], views' position may show direction (e.g., using reading order) [11, 24], or a line may connect the right side of a source view to the left side of a destination view [80]. Similarly, views' component hierarchies may show direction. For example, a line from a data bar to a view show direction implicitly. This suggests that representations of directionless relations might focus on showing relations between components at the same level of the component hierarchy (i.e., data to data, meta-data to meta-data, or view to view).

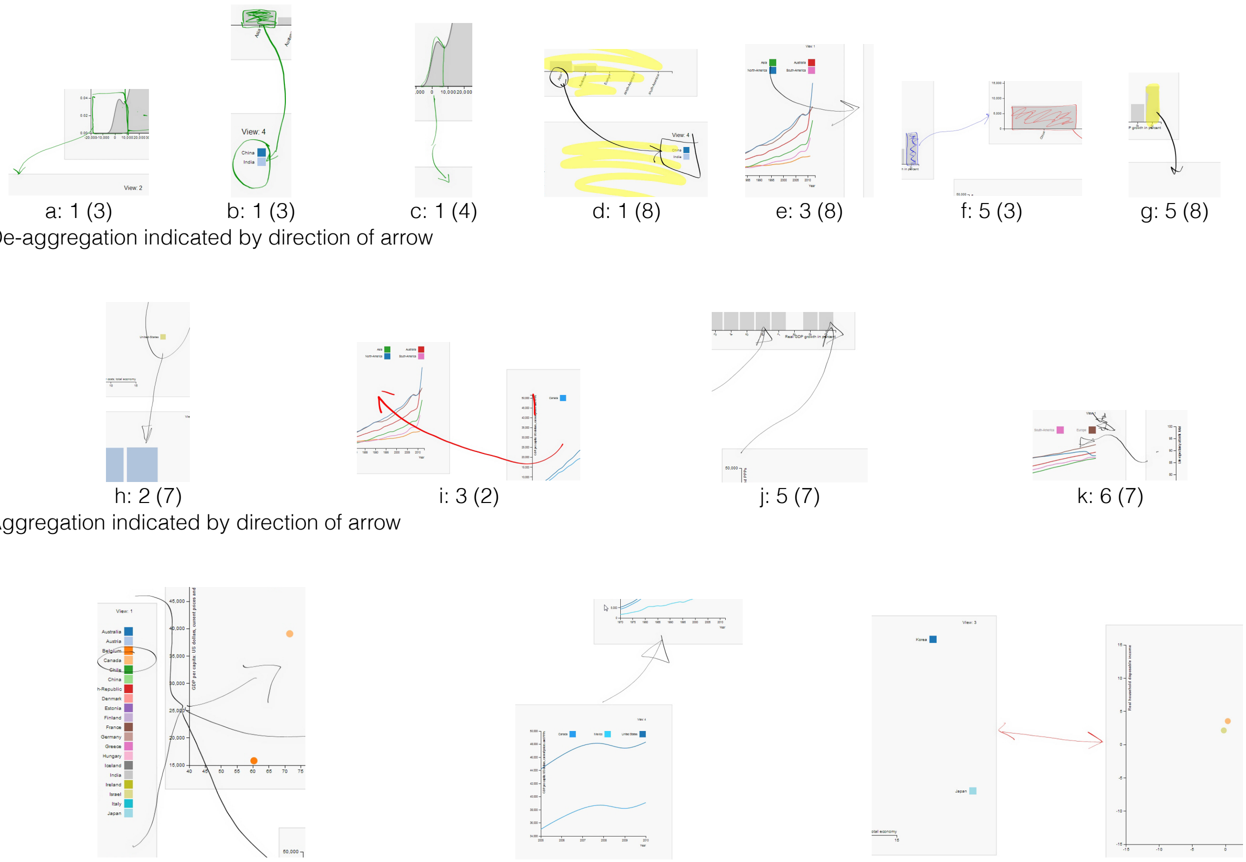


PanoramicData [167]

Explates [80]

Figure 7.14. Literature examples of showing directions of relations between views.

Many study participants considered the direction of views' relations. We observed this from participants' verbal considerations, their gesticulations, and their sketches. Examples include considering that some marks "make you read the visualization in a specific order"; stating "I am reading it left to right, top to bottom" while arranging views; or stating "so this takes that data over there [pointing with both hands]", and showing with hand gestures how views connected, suggesting that the visualization was "trying to tell a story". Many participants indicated directions explicitly by sketching arrows. For example, they drew these between data bars and legends. Here, participants suggested these showed less direct connections between data in the two views. Figure 7.15 shows examples of such sketches grouped according to the different aspects of indicated relations (a-g: de-aggregation, h-k: aggregation, l: filtering, m: zooming, and n: encoding similarity). The figure shows disagreement between arrow directions. For example, some participants drew arrows leading to, while other participants drew arrows leading from, de-aggregated views.



a: 1 (3) b: 1 (3) c: 1 (4) d: 1 (8) e: 3 (8) f: 5 (3) g: 5 (8)
De-aggregation indicated by direction of arrow

h: 2 (7) i: 3 (2) j: 5 (7) k: 6 (7)
Aggregation indicated by direction of arrow

l: 4 (6)
Filtering indicated by direction of arrow

m: 3 (7)
Zoom out indicated by direction of arrow

n: 2 (4)
Encoding similarity and mergability indicated by bi-directional arrows

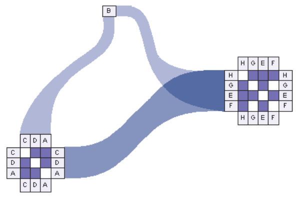
Fig. 7.15. Examples of participants' use of line arrows to indicate different aspects of relations. The text below each subfigure indicates the occurrence of sketches as "subfigure: scene (participant)".

7.2.5 Strength

Strength of relations captures that view relations can vary from weak to strong. Relation representation can show this. This dimension is similar to the notion of edge weights in graph data. *Strength* may comprise both negative and positive values, thus implying that representations may show that two views are related *or* unrelated, for example to show that two views that look similar are actually different. Any relations between views can influence how to show strength, such as interactions with the system (e.g., brushing, proximity data, and user profile) and the visualized data (e.g., amount of common data points). Additionally, combinations of relations can be part of numerical computations of strength, which visual representations can show directly. Alternatively, they might influence when to show a relation. Most systems show strength implicitly by showing a subset of possible relations, based on an assumption of a static importance metric. For example, hovering over data points to highlight related data points (i.e., brushing and linking) uses binary interaction data (hover/not hover) to show binary relation strength (highlight/don't highlight).

Elzen & Wijk [41] and Henry et al. [62] used aggregate links in which size encoded number of links between views (in what is described as an overview) and adjacency matrices, respectively. Figure 7.16 show these.

Elzen & Wijk [41]



NodeTrix, Henry et al. [62]

Figure 7.16. Literature examples of showing the strength of views' relations.

In the study, we mainly observed participants implicitly talk about view relations' strength. When participants talked about weak relations, they expressed that they were "weak" or "not strong", whereas when talking about strong relations, they expressed that they were "important". A participant for example stated "This connection is not strong" regarding a relation between two bar charts in scene 5 (see Figure 7.24) that showed the same data with different aggregations.

Participants also sketched relation representations that conveyed strength. For example, a participant used curvy or dotted lines to signify weaker relations than straight lines (see Figure 7.17).

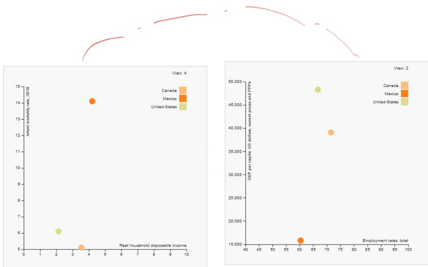
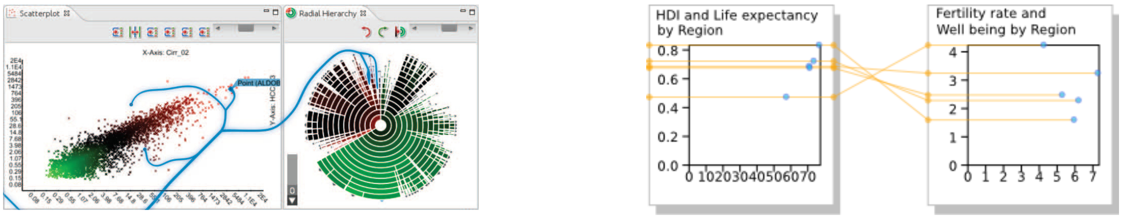


Figure 7.17. Example of showing the strength of views relations. The sketch occurred with participant 4 in scene 4.

7.2.6 Interference with views

Interference with views captures that view relation representations may interfere with within-view representations. It is thus important to consider this in designs of relation representations. For example, to reduce interference, designers may consider the spatial layout within views by routing lines around data points. Similarly, merging lines, connecting to labels rather than data points, or aligning lines to axes or borders, can reduce interference. Additionally, colour used to show view relations might interfere with within-view representations. For example, if using conflicting or strong colour encoding, these may take focus from the data shown within views.

Steinberger et al. [137] routed lines along view borders to reduce occlusion of salient regions. Similarly, Viau & McGuffin [151] fixed lines between data points to axes and view borders to reduce clutter. Figure 7.18 show these.



Steinberger et al. [137] ConnectedCharts [151]

Figure 7.18. Literature examples that considered relation representations' interference with views.

In the study, participants considered how meta-view visualizations could interfere with within-view visualizations. We divided these concerns in two groups: first, clutter caused from showing many between-views relations, by hiding or cluttering the data shown within views, and second, added visual indications of view relations that decrease peoples' ability to focus on or understand data shown within views.

Examples of the first concern included participants connecting lines from data bars in a bar chart to legends in a scatter plot instead of connecting to data points, to reduce clutter; using transparency for links between data bars and data points; and expressing concerns for using the same color, to encode different things, across many views.

Examples of the second concern included participants' consideration that highlighting a views' border and axes in scene 3 (Figure 7.22) to indicate an overview plus detail relation between two views took focus from the data in the detail view; and concerns about between-view lines connected to within-view lines in scene 3. In contrast to the first concern that considered the amount of shown relations, this concern highlighted that few, but poorly designed between-view representations can negatively affect comprehension.

7.2.7 Summary

I described a framework that offers six dimensions of view relations and their representations.

In describing the framework, I have connected it to related work as well as the many novel view relation techniques that we observed in the study, based on an analysis of the collected study data using Grounded Theory [139]. However, where the analysis focused on the range of thoughts and ideas that participants expressed and sketched, the framework considers view relations in terms of possibilities for using between-view meta-visualizations.

The dimensions aim to help design and evaluate concrete meta-view relation representations. However, the dimensions are loosely orthogonal. This implies that it is possible to design for one dimension at a time, although it may be more effective to consider the dimensions together.

Note, that although the dimensions describe important aspects of view relation representations, they do not describe all relevant aspects. Most importantly, the dimensions do not describe the style of the representations.

Next, I demonstrate the framework used to describe an existing design.

7.3 The framework in action

Researchers and designers can use the framework dimensions to describe existing relation representations and to generate new ones. Existing literature contains many examples of showing combinations of these dimensions. To show the descriptive power of the framework, I traverse the framework by walking through the position of Semantic Substrates [130] in figure 7.19. I use Semantic Substrates for three reasons: a) it relates to many aspects of the framework; b) it is well-known (more than 200 citations) and cited in many related papers; and c) it is relatively easy to understand the visualizations and interactions described in the paper. By traversing the framework, I demonstrate how it is possible to consider each dimension in turn, with respect to showing between-view relations.

In the framework diagram (Figure 7.19), Semantic Substrates [130] is shown at the top-left hand of the list of related literature. To understand the walk-through, I refer the reader to Figure 7.10, which show a screenshot of the Semantic Substrates (SS) system.

Design intent: Following its brown line from left to right, SS is marked as intending to show data and encoding. SS shows data relations since it links data item to data item. Further, it shows encoding relations when it reduces links between the views to specific regions of the views.

Visual components: SS is marked as using both data, meta-data, and view components. SS connects data points to data points, connects a rectangle that is linked to the axes, which is thus a meta-data component, and finally, it connects view components with link colour.

Re-use of view representations: SS is marked in the middle in re-using view representations, because there is no apparent re-use of within-view representations.

Direction: SS is marked at the top of direction in the framework diagram. We did so because the data visualised with SS was directed, because the authors stated that they aimed to show links' direction, and because SS actually represented direction with arrows.

Strength: SS is marked in the middle of the strength rectangle in the framework diagram. We did so because SS shows or hides links (binary strength) based interactions, and does not communicate strength based on a system-based weight.

Interference with views: SS is marked towards the middle of the framework diagram. We did so because SS uses node-link diagrams, which are known to result in clutter. However, we positioned it closer to the middle than the top of the framework diagram, because SS's interaction technique reduces clutter.

7.4 Summary and conclusion

In this work, we studied the varied relations that exist between visualization views, and the possibilities for showing them. In the previous sections, I described our framework of view relations, which I also used to describe the findings of our study. The framework encapsulates many of our findings.

I believe the framework is relevant in both design and evaluation. First, I believe it is useful in a design process, where designers can use it as a catalyst for creating novel between-view meta-visualization and interaction techniques. Second, I believe it is valuable in evaluating and improving existing between-view meta-visualization and interaction techniques.

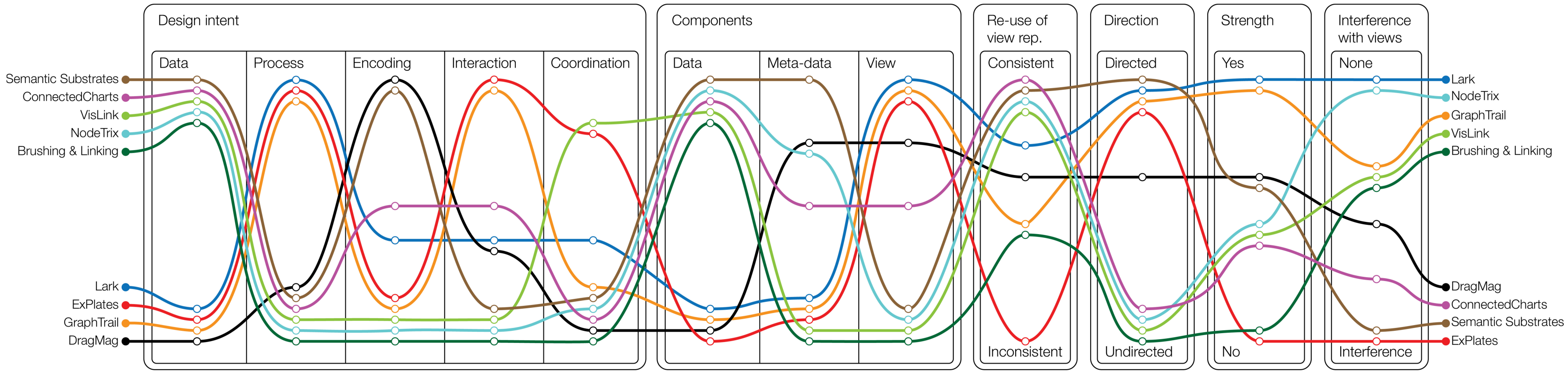


Figure 7.19. Overview of framework dimensions used to describe related work in terms of the framework. For design intent and components, top means that the work considers the dimension. When work is not positioned top or bottom in a dimension, the dimension is only partly considered. Here, Semantic Substrates is exemplified. Design intent: Semantic Substrates shows data relations since it links data item to data item. Further, it shows encoding relations when it reduces links between the views to specific regions of the views. Visual components: Semantic Substrates connects data points to data points, connects a rectangle that is linked to the axes, which is thus a meta-data component, and finally, it connects view components with link colour. Re-use of view representations: Semantic Substrates has no apparent re-use of within-view representations. Direction: The data visualised with Semantic Substrates was directed, the authors stated that they aimed to show links' direction, and Semantic Substrates actually represented direction with arrows. Strength: Semantic Substrates shows or hides links (binary strength) based interactions, and does not communicate strength based on a system-based weight. Interference with views: Semantic Substrate uses node-link diagrams, which are known to result in clutter. However, we positioned it closer to the middle than the top of the framework diagram, because Semantic Substrate's interaction technique reduces clutter.

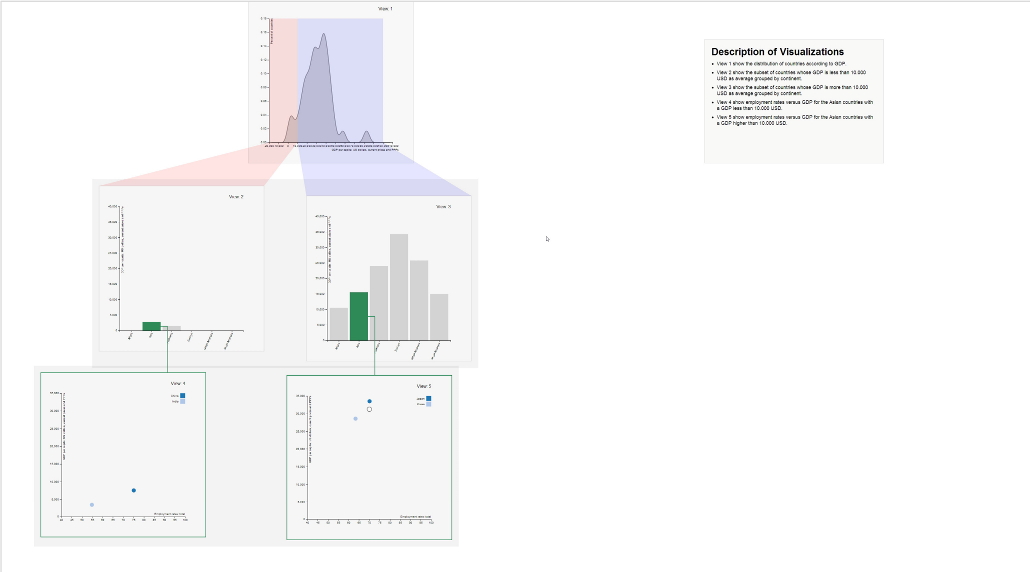


Figure 7.20. Scene 1: View 1 shows a histogram of GDP, which is divided in two areas by shading. These areas connect to view 2 and 3, which show bar charts of GDP grouped by continent, for countries that are shaded in view 1. A line connects the Asia data bars in view 2 and 3 to the border of view 4 and 5, which show scatter-plots of employment rate vs. GDP for Asian countries. View 2 and 3, and 4 and 5 are surrounded by areas indicating hierarchy.

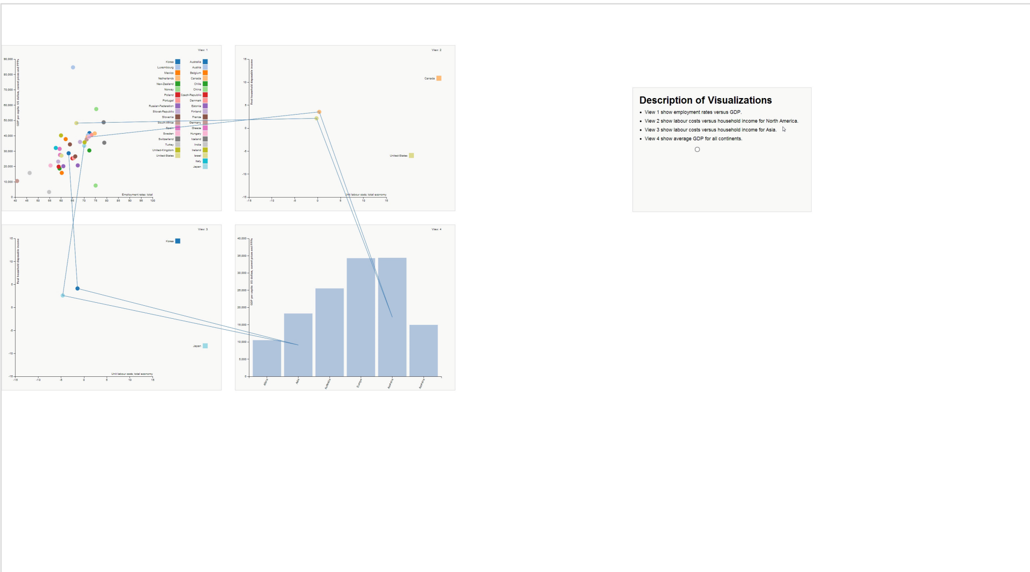


Figure 7.21. Scene 2: View 1 to 3 show scatterplots. View 1 shows employment rate vs. GDP. View 2 and 3 show labour costs vs. household income for North America and Asia respectively. View 4 shows a bar chart of GDP grouped by continents. Lines connect data points in view 1 to 3, and data bars in view 4. Scatterplot legends share spatial encoding.

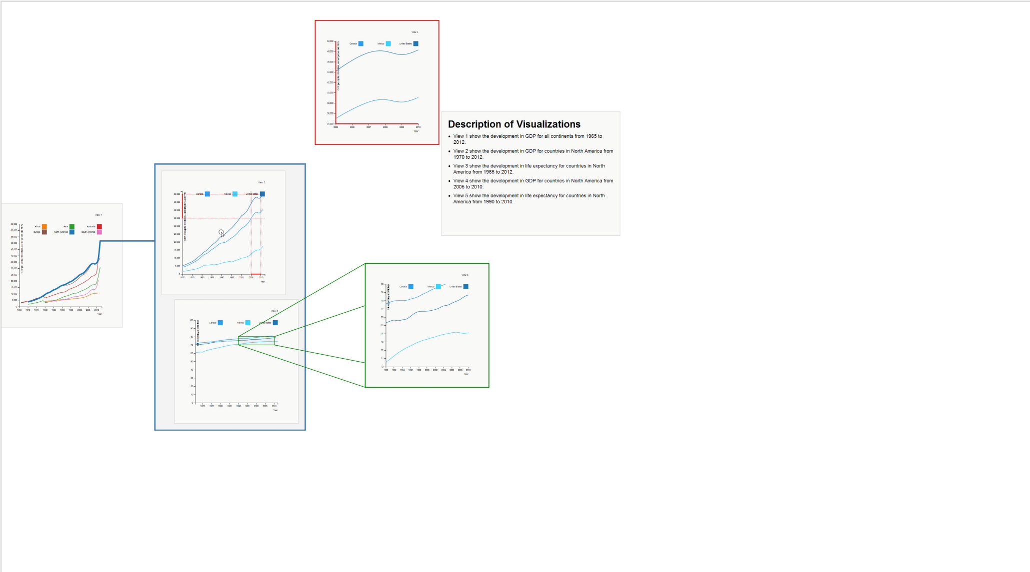


Figure 7.22. Scene 3: View 1 shows a line chart. The blue data line in view 1 connects to a rectangle surrounding view 2 and 3 with a similar blue line. View 2 and 3 show line charts of de-aggregations of the blue line in view 1. View 4 shows view 2 in detail. The axis ranges shown in both views are red. Lines indicate the area in view 2 that is shown in view 4. View 5 shows view 3 in detail, indicated by a box in view 3 connected to view 5.

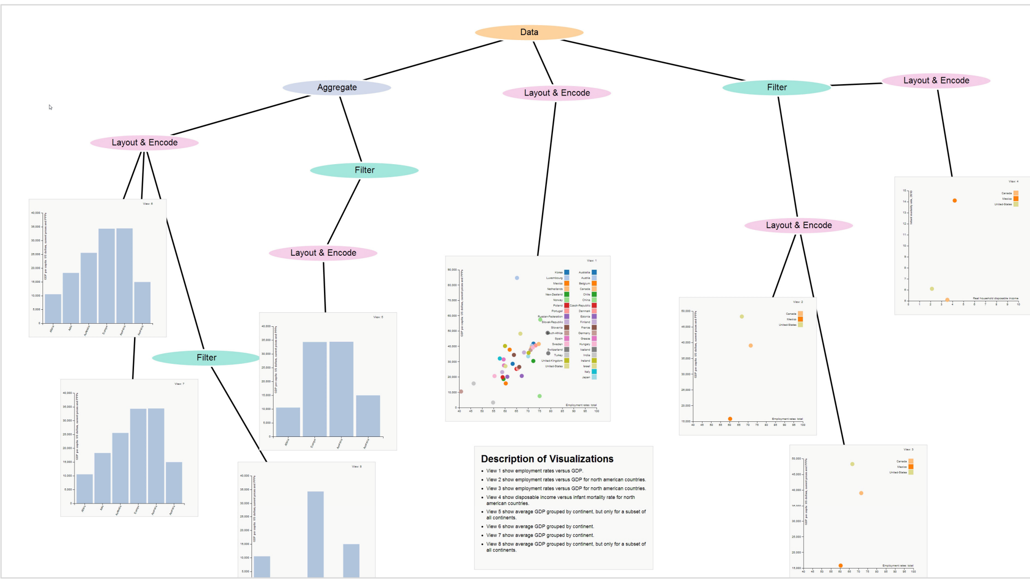


Figure 7.23. Scene 4: View 1 to 4 show scatterplots. View 1 to 3 show employment vs. GDP, but view 2 and 3 only for North American countries. View 4 shows household income vs. infant mortality for North American countries. View 5 to 8 show bar charts of GDP grouped by continent, but view 5 and 8 for a subset of continents. Views are connected to circles, which represent data processes. The orange circle represents data and connect to other circles, which in turn connect to views. The pink, blue and green circles represent layout/encode, aggregation, and filter.

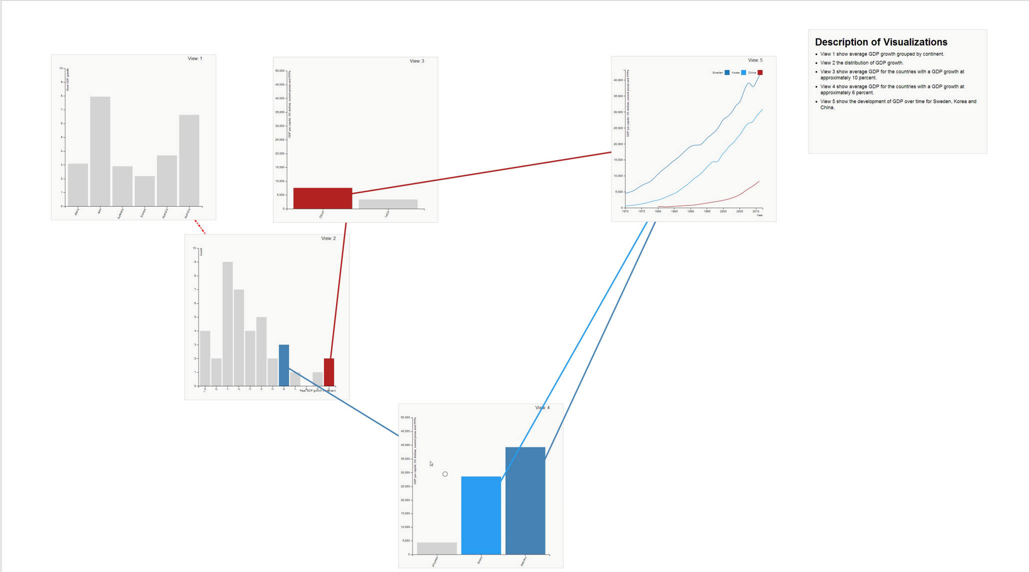


Figure 7.24. Scene 5: View 1 to 4 show bar charts. View 1 shows GDP growth grouped by continent. View 2 shows distribution of GDP growth for the same data as view 1, indicated by a dashed red line. View 3 and 4 show GDP for countries with a GDP growth at approximately 10% and 6%, respectively. Data bars in view 2 for those percentages connect to view 3 and view 4 respectively. View 5 shows development of GDP over time for Sweden, Korea and China. The countries' in view 3 and 4 connect to view 5 using lines coloured similar to the countries.

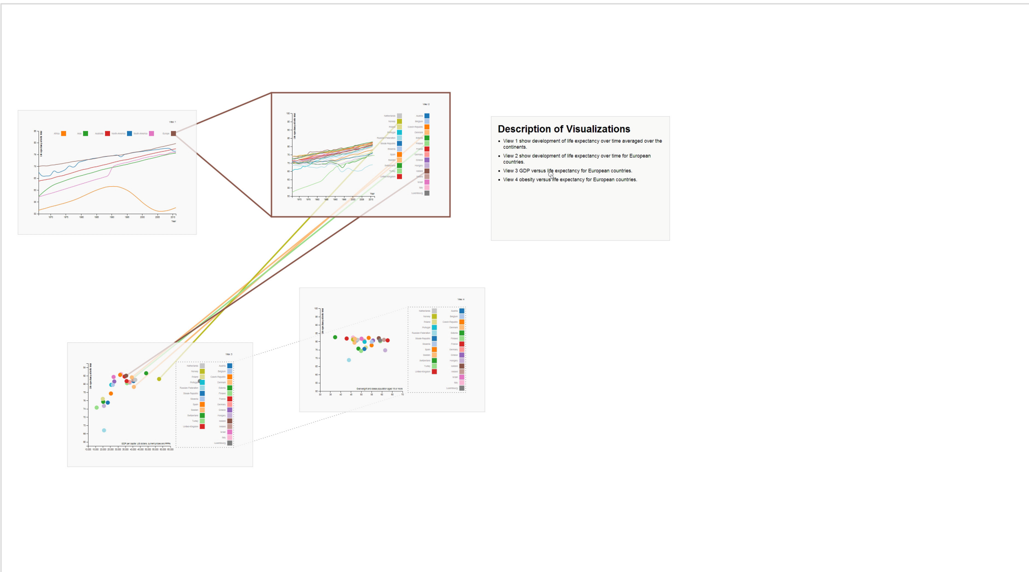


Figure 7.25. Scene 6: View 1 and 2 show line charts of life expectancy over time for continents and European countries, in view 1 and 2 respectively. Lines connect the legend item Europe in view 1 to view 2's border. Scandinavian countries in view 2's legend connect to these countries' data items in view 3, which shows a scatterplot of GDP vs. life expectancy for European countries. View 4 is identical to view 3, except the horizontal axis show obesity.

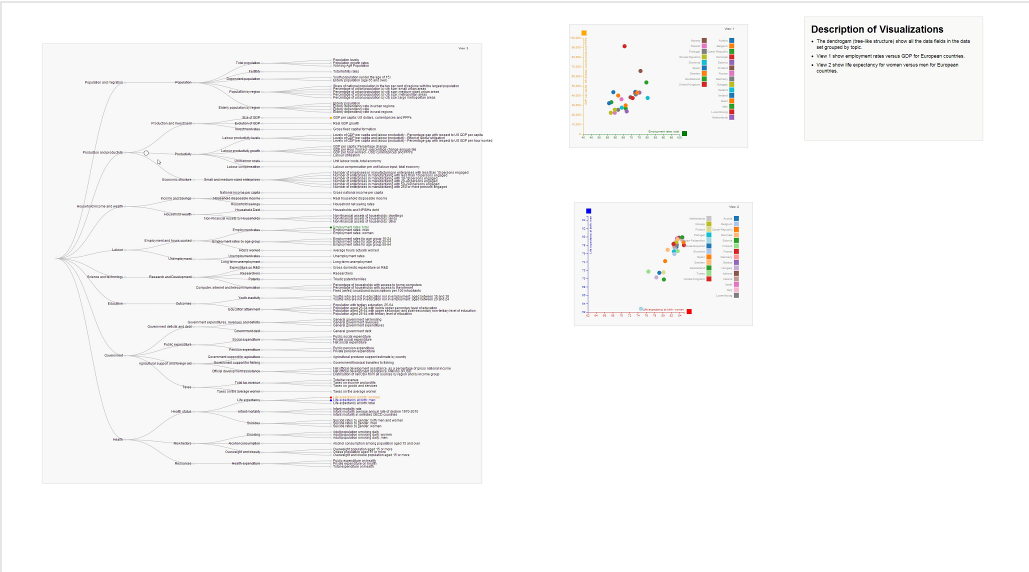


Figure 7.26. Scene 7: View 1 and 2 show scatterplots of employment rate vs. GDP and life expectancy of men vs. women, respectively for European countries. View 3 shows all data fields in the given data set grouped by topic. Fields in view 3 that are encoded in view 1 and 2 are highlighted in all view 1 to 3.

Part III
Conclusion

Chapter 8
Discussion

In this chapter, I discuss the findings from my PhD research, as well as its methodology, in terms of how these answer the research question. I defined this in Chapter 1 as:

> *How may abundant display space support visualization-based data analysis?*

I base the discussion on the four papers and their respective studies, which I described in Part II. First, I discuss my findings. Then, I discuss my choice of methodology.

8.1 Findings

In this section, I discuss the findings of the four papers described in Part II. These comprised the majority of my PhD research. In discussing the findings from the individual papers, I aim to synthesize the findings of the individual contributions, and then compare this to related work.

First, I discuss the choice between using abundant display space for few large visualizations and many small visualization views (8.1.1). This leads to considerations of interaction (8.1.2) and visualization (8.1.3) between views, and the tasks (8.1.4) associated with this consideration. Then, I discuss the span of time in relation to abundant display space (8.1.5). The last area of insight relates to people's physical movements in relation to large displays (8.1.6). Finally, I discuss open issues (8.1.7).

8.1.1 Two possibilities emerge with increased display size

When we, as visualization and interaction designers, increase the size of displays, two principal options emerge. Either we can fill the display with one large visualization, or we can display many smaller visualization views, and let users arrange these to make sense of data. The front-page of the present thesis illustrates the option of showing many smaller visualization views. I believe that this choice is principal, and that understanding this is the most important, simple, and striking insight in my work.

Filling the display with one large visualization gives room to subdivide the space into what we can consider as separate views. This is done by e.g., Yost et al. [166]. This option leaves the choice of spatial encoding to the designer, who may thus use this encoding to communicate the relations between individual views. By displaying many smaller visualization views, we let users arrange these to make sense of data. This is done by e.g., Tobiasz et al. [143]. This option leaves the task of communicating views' relations to the designer, primarily using alternatives to spatial encoding.

Clearly, while these two options delimit the potential extremes of visualization views' size, it is also possible to use them in combination. For example, by showing small views as overlays on top of a large visualization that fills an entire display. Participants considered this possibility during a workshop in the study described in Chapter 4 (Paper I).

I have studied both options in my work. In Chapter 4 (Paper I), we did not code for these options in our analysis. In retrospect however, the collected data showed this dimension. Instead, we described themes that related to each of them individually, as well as combined. In Chapter 5 (Paper II), we focused on showing few large visualizations. In Chapter 6 and 7 (Paper III and IV), about F3 and visualization view relations, we focused on using many small visualization views.

My focus has thus mainly been on using many small visualization views. This changes the manifestation of abundant display space. Thus, abundant display space turns view-considerations into meta-view considerations (i.e., considerations about or beyond the view). This turns the focus to letting users create new visualizations effectively (Chapter 6, Paper III) and showing meta-visualizations of their relations (Chapter 7, Paper IV).

I discuss these foci in the next sections:

Section 8.1.2: Focus on interaction with views as a meta-concept. I base this discussion primarily on how F3 enabled data exploration by means of interaction and the findings in Chapter 6 (Paper III).

Section 8.1.3: Focus on showing relations between views as a meta-concept. I base this discussion primarily on visualizations between views (i.e., meta-visualizations), which I described in Chapter 7 (Paper IV).

Section 8.1.4: Focus on tasks related to using many views as a meta-concept. I mainly discuss this in terms of related work, and specifically in terms of the limitations in using related work in this context.

8.1.2 Data exploration with abundant display space

Exploration of data is central to how abundant display space can support data analysis with visualizations. Here, I consider data exploration to mean the generation of hypotheses from data, discovery of new insights in data, and looking through data to understand the distribution of certain characteristics (comparable to Brehmer & Munzner [21] *explore* and Tukey's [148] notion of *exploratory data analysis*). While much other work has looked at this, most of these consider either fixed spatial layouts (e.g., [166]) or take data to mean textual documents (e.g., [3]).

I believe the results described in Chapter 4 (Paper I) show vividly how abundant display space might support data analysis, for example based on *trail of thoughts*. In the studies described in Chapter 5 (Paper II), participants used the space in front of the displays to explore data and described the physical space by how they explored it (e.g., *"Let me see what is out here"*). Chapter 6 (Paper III) showed concrete data exploration possibilities with many visualization views. Likewise, Chapter 7 (Paper IV) considered the relations between such views, which I believe benefit data exploration greatly.

Creating and extending views

The way that people interact with and between views is relevant in considering the way that abundant display space supports data exploration. I argued above that studying this is a sort of meta-concept, and that it goes beyond looking at interactions with the view (e.g., as in Sadana & Stasko [122]), but rather looks at the process of moving from view to view. This was our focus in designing the interaction techniques for F3. Our aim was to examine the possibilities for quickly creating new views, expanding existing views, and combining parts of views, to allow people to explore data.

For example, the interactions facilitated:

1. Juxtaposing views, by positioning views side by side by using the explore interaction for two parts of a visualization. Gleicher et al. referred to this as spatial juxtaposition [50].
2. Breaking down views in small multiples [146], by using F3's explode interaction technique.

In doing so, interacting with the visualization views became different to how people otherwise interact with visualizations: the focus was on using views to interact with other views. It was thus not visualization interaction, but meta-view interaction – interaction beyond the individual visualization views. While this approach is present in related work (e.g., [143]), in F3, the visualizations shown within the views were important parts of the interaction.

Views as toolboxes

A specific concept of meta-view interaction concerns the use of views as toolboxes. These views provide little value except for helping other exploration steps. I believe that abundant display space is central in enabling people to use auxiliary views as toolbox views, and conversely, that given less display space, using views as toolboxes is a wasteful use of the limited amount of pixels and display area.

Beaudouin-Lafon [12] offers an approach to understand the use of views as toolboxes, which I discuss in the following based on Chapter 6 (Paper III). As a reminder, in F3, analysts used some views as toolboxes, to interact with, and thus filter other views. For example, in looking at admissions across hospitals in the capital region of Denmark (hospital view), analysts used a toolbox view that showed the distribution of admissions across all patients' age (age view). By dragging the 0-9 year data bar from the age view and onto the hospital view, they filtered the hospital view by age. Keeping the view around for later analyses emphasized its use as a toolbox view.

In Beaudouin-Lafon's terms, a view that has an analyst's focus, show *domain objects*, here visualized data. Constructing a secondary view (a toolbox view) to filter the first view in focus, creates a *meta-instrument*, and briefly shifts the analyst's focus to this secondary toolbox view as the *domain object*, in a *reification process*. The toolbox view itself is a *first-class object*, since every operation that was possible on the initial view is possible on the *meta-instrument*. This is analogous to a painter that shifts focus towards the colour palette *(meta-instrument)* after painting strokes on a canvas *(domain object)*. The palette becomes the painter's focus through *reification*. The palette is a first class object, since every operation that was possible on the initial view is possible on the *meta-instrument*. For example, the palette allows the painter to use the brush on the palette, just as she used it on the canvas.

In dragging data bars from the second toolbox view, the user abstracts the data bar from a *domain object* to a representation of the data (the inverse of Beaudouin-Lafon's *reification*). The representation of this abstraction is an *instrument*. Here, the alternative release areas infer the resulting action of the *instrument*. This is analogous to a carpenter picking up a hammer, after having repaired it, and hitting either a nail, or a finger – different resulting actions of the *instrument*.

Dropping the data bar on the original first view filters it, which completes the original domain task and returns to the original view as the *domain object* once again.

Simplicity and complexity

In Chapter 6, I described various ways that users could combine views with F3. I discussed these possibilities above. The simple and advanced interactions offered many ways of conducting complex analyses. In a way, it seemed as if participants preferred using these interaction techniques over the more complex interaction techniques, even though these would provide the same results faster. For example, the trail cloning technique is complex compared to the other techniques. This technique offered a fast method of repeating analysis steps for a different set of data. However, during the deployment, I saw analysts construct similar trails with more manual techniques. This might be due to several reasons:

1. Lack of training: Analysts might not be aware or understand the complex techniques, and be able to recognize situations where they are useful.

2. Lack of overview of analysis: Analysts might not realize the aim of their analysis at first, and would thus not be able to specify their goals before initiating the manual process.
3. Value from manual process: The act of constructing the trail brought additional value to the analysts. The value could be added insights, understanding the context of data, etc.
4. Complex techniques restrict analysis: The complex interaction techniques restricted analysts too much, by limiting the range of approaches.

The two-week duration of the deployment study of F3 allowed analysts to gain confidence with the system. However, I do not believe their level of expertise plateaued towards the end of the deployment. Therefore, I believe that lack of training was a factor in the observations, and thus, in which interaction techniques the participants used. However, some analysts attained high familiarity with some techniques, which allowed them to articulate complex analyses with less complex techniques. Therefore, I believe the second, third, and fourth reasons above are more likely, and believe that the less complex interaction techniques provided the best possibilities for analysts to work with data.

Additionally, I believe that the design of F3's Explode and Matrix Creation techniques was weak. The additional user interface components introduced by these interaction techniques resulted in more complexity than necessary. Ideally, these interaction techniques should create several views that are similar to other views. If necessary, the techniques could group the created views in a single rectangle, from which analysts could arrange them freely, thus supporting "space to think" [3]. This design would keep the simple properties of views, offer a more consistent design, and allow analysts to combine views created by these techniques to conduct complex analyses.

Benefits of space for exploration

Does abundant display space benefit exploratory data analysis? I believe that my research has shown that given properly designed user interfaces, abundant display space benefits exploratory data analysis for a range of tasks and contexts. Specifically, I believe that the findings discussed above shows the possibilities for using abundant display space to support collaborative and exploratory data analysis, which has limited support with desktop-sized displays. Thus, this offers an advantage over existing possibilities.

I see toolbox views as related to exploratory data analysis. The use of toolbox views outlines promising possibilities for using periphery space to show aspects of data, which might not require attention by analysts, but provides context for the current focus. An analyst in the deployment study of F3 highlighted this: *"If you are looking into a specific problem, seeing the context is important"*.

Trail of thoughts

When showing more than a few views using abundant display space, it is crucial to support analysts in understanding how views are related. The findings from the introductory studies of F3 (described in rows 4 and 5 in Table 6.1) in Chapter 6 (Paper III) suggested the importance of this. In the studies, we observed that participants had trouble remembering views' relation without support for understanding the relations. They needed this to understand the contents of individual views, which did not convey all information. If every view had shown all information, understanding the relations would probably have been less crucial to participants. However, showing all information in every view, would defy the idea of showing many views. Additionally, in fixed spatial layouts as argued above, the layout can provide implicit or explicit clues of relations between views. In allowing users to arrange views freely, designers of visualization tools leave the freedom for the users to master. Therefore, when designers cannot communicate views' relation through spatial positioning, they will have to provide other clues.

In this section, I described and discussed meta-view interaction based primarily on the studies of F3 in Chapter 6 (Paper III). I believe my observations have shown that people need to understand views' relations when working with many views. Thus, systems that use many visualization views should support this. In F3, we showed one possibility for showing views' relations. I realized that many other possibilities existed, and thus opted to study this in more detail. This resulted in the study of representing view relations, which I described in Chapter 7 (Paper IV). This study focused, not on meta-view interaction, but on meta-view visualizations. I discuss this aspect in the next section.

8.1.3 Understanding views' relations with abundant display space

With abundant display space, there is room to show many views. Doing so creates a need to understand how the views are connected.

Participants in the workshop study which I described in Chapter 4 (Paper I), considered showing relations between visualization views. We identified some of these as *trail of thoughts*. In designing F3 and during the studies described in Chapter 6 (Paper III), I observed and experienced how difficult it is to conduct analyses without proper support for understanding views' relations. For example, in the initial studies of F3 (described in rows 4 and 5 in Table 6.1), the system did not show relations. In these studies, participants got confused when looking at views that showed related data with no indications of the views' relations. I believe these observations and experiences show that people need to understand views' relations when working with many views. Thus, systems that use many visualization views should support this.

These insights inspired me to design F3's relation representations, which I described in Chapter 6, as well as the study that I described in Chapter 7. In Chapter 6, I showed one possibility for showing views' relations. In Chapter 7, I described our study on the many different possibilities for representing view relations. This study focused, not on meta-view interaction, but on meta-view visualizations.

From these insights, I argue that it is important to represent view relations. While I believe there is value in showing views' relations, many systems do not show these. However, they still support a range of user's tasks sufficiently. For example, Isenberg & Fisher [68] and Andrews et al. [3] showed minimal relations between document views. Andrews et al. [4] later described the Analysts Workspace, which showed the documents' relations. Additionally, most visualization systems for multi-display environments show no relations between views (e.g., [18, 44]), and, no ubiquitous desktop user interfaces show window's relations. The few windows and rare apparent relation between them might explain this.

Framework of View Relations

As I have described, systems exist that do not convey views' relations and still support people in working with a range of tasks. It is a design choice which relations, if any, to convey. The study on view relations described in Chapter 7, outlined different reasons for showing views' relations. We identified these as the Design Intent dimension, and divided them in five groups (data, process, encoding, interaction, and coordination). The Design Intents answer why analysts need to see relations. I do not believe the literature that describe visualization tasks and taxonomies match the Design Intent dimension, and further believe, that this is due to the abstraction level of the tasks supported by meta-view visualizations, and thus the Design Intent dimension.

Is it always a good idea to show views' relations? I believe that showing view relations is a requisite when designing systems that allow users to arrange views freely. In doing so, designers give up the possibility of a coarse-grained spatial encoding in trade for users' freedom to arrange views. Designers do this to facilitate sense-making with "space to think". Therefore, systems need to show views' relations using other visualization techniques than spatial encoding (e.g., use of links, colour, etc.).

I believe that we identified the most important design intents, but that future research might identify additional design intents. More importantly however, I believe that there are many unexplored possibilities within the five design intents we described. For example,

- Few systems show data relations without using data components,
- Few systems show encoding relations, and
- Few systems show coordination relations.

Even though it seems important to show view relations, systems that do this might not need to show them constantly. For example, peoples' interaction might show or hide relation representations. Brushing and linking is an example of this. We did not aim to cover this in our study of view relations. Many participants however, did consider this aspect, which shows the priority it had to participants. For example, participants considered this in terms of its potentials for reducing clutter. We chose not to include it in the framework, because we did not consider it as a conceptual decision relating to view relations, but as a design choice. However, other aspects of these methods are considered in the framework under the coordination design intent.

The remaining parts of the framework cover what the relation representations show and how they show it on a conceptual level. We deliberately left out many specificities of how systems may show view relations (e.g., choice of colour, line and arrow style, animations, etc.), because of the wealth of design options. Similarly, we omitted details that we thought were of too limited use. For example,

- If designers aim to show data relations between scatterplots, they might choose to connect legend items instead to reduce clutter. This causes indirection – showing what one wants to convey indirectly. I believe a separate dimension might explain this better than the Visual Components and Interference with Views dimensions.
- If designers use visual means to group views (e.g., rectangles), relations might use these in relation representations. These visual means concern meta-view components, and would thus comprise a fourth group in the visual components dimension. Instead, we consider them visual means to show individual views' relations.

In short, I believe the framework represents the most important aspects of view relations and their representations, but that many additional considerations should be part of designing systems that show relations between views. Next, I discuss possibilities for improving the usefulness of the framework, and show its value to visualization researchers and designers.

Limitations of the Framework of View Relations

I believe that we covered aspects of view relations that are important, and in comparison to related work (e.g., [79]), have used a broader approach to integrate the many different ways that views might be related. Aiming for such an overview necessarily leaves out details, which future work can address. In the following, I consider four such omissions.

First, the framework lacks a formal notation. To describe relations, we need a succinct notation. I believe this will improve the usefulness of the framework and for example allow: 1) implementation of interactive web-based systems that describe the framework; 2) structured comparisons of techniques for representing view relations; and 3) structured descriptions of related work. This leads us to the next point.

Second, the framework lacks a structured grounding in related work. While Figure 7.19 shows eight systems that represent relations between views, many additional systems fit the dimensions of the framework. In addition, each described system may use different relation representation techniques, which the simplistic figure presentation does not reflect. For example, GraphTrail [37] conveyed different relations in different colours, which might be shown with different lines in the framework figure.

Third, I did not demonstrate the framework's usefulness in designing view relation representations. We argued that the framework might be useful as a design tool, but I leave it to future work to demonstrate the actual value.

Fourth, we mostly ignored interactivity in our study on view relations, both in terms of (1) the effects of view interactions on relation representations and (2) potential interactions with relation representations. Part of the reason for these omissions, is the limited amount of interactions that was possible to set up in the context of a study that aimed to provide an overview of possibilities. Thus, these points are obvious next steps to explore in designs and studies.

Next, I discuss tasks related to working with many views, which relates to both meta-view interaction and visualization.

8.1.4 Tasks related to working with many views

In designing and describing F3's interaction techniques, I considered existing visualization task taxonomies and typologies. Brehmer & Munzner's multi-level task typology addresses both the reasons that people perform tasks, as well as the details pertaining to how they solve them. In my opinion, this typology is the most useable tool to understand visualization tasks and interaction, because it covers both the reason, the means, and the relation between input and output of users' tasks. However, I struggled to fit it to the meta-view interactions of F3. For example, it offered no sensible approach to describe these F3 scenarios (emphasis indicates concepts in Brehmer & Munzner's [21]):

- An analyst looks at a view that show distribution costs across regions. Interested in looking at these costs for a specific region, the analyst uses F3's explore technique, to create a view showing costs across hospitals in the specific region.

  In this scenario, the analyst *produces* a new view by *deriving* data from the existing view. However, while *derive* should be persistent, this was not the case with F3 or the way that analysts used it.

- An analyst looks at an existing view that shows general costs across a range of regions. Interested in looking at these distributions for children, the analyst first creates a new view next to the existing view. The new view shows patients' ages in predefined age groups. Then, the analyst drags the "children" group from the new view, to the existing view to filter by age.

  In this scenario, the analyst *produces* a new view to *filter* the existing view. However, while F3 preserves the analytical provenance by *recording* it, this is a by-product of the interaction rather than the analyst's intention.

Attempting to use the existing task taxonomies and typologies to describe the aim of F3's interaction techniques proved unfruitful, as evidenced in the scenarios above. I believe one reason for this, is that many tasks related to views, are meta-level tasks. Users conduct these, not to arrive at an analytical understanding, but to lay the foundation for carrying out domain tasks (on *domain objects* [12]).

In our study described in Chapter 7 (Paper IV), this became more apparent, which is also shown by the design intents dimension.

I have argued above that we focused on meta-view interaction in Chapter 6 (Paper III), and meta-view visualizations in Chapter 7 (Paper IV). Together, these two foci span a range of possibilities for conducting many meta-analysis tasks. In Paper IV, we described "Design intents" for meta-view visualizations. I see this as a first step to understanding what comprise tasks related to meta-view visualizations.

I believe that the focus on meta-view interactions is to some extent incompatible with the existing task taxonomies and typologies, and thus argue, that the value of these is limited for such situations. In short, the vocabulary available to discuss tasks related to meta-view visualization and interaction is limited.

These considerations end my discussions on matters related to meta-view interaction, visualization, and their associated meta-analysis tasks. Next, I discuss duration of interactions with the concepts of persistent and transient user interface elements.

8.1.5 Duration of interactions: Persistent and transient

Much of my work has implicitly considered the duration of interactions and user interface elements. In the workshop study described in Chapter 4 (Paper I), we identified persistency as an important theme. Here, participants imagined setting aside areas of a display for persistent views. Additionally, we identified a theme that related to temporarily using large parts of a display for menus. Views in F3, which I described in Chapter 6 (paper III) were persistent when used to segregate data in secondary views, according to Brehmer & Munzner's definition [21].

Above, persistency obviously expressed that a part of the display does not change. Likewise, transience obviously expressed a short temporary change in a part of the display. The contention here is that we described both the persistence and transience in unbounded terms. What does it mean that the display does not change?

- does it mean that the display state is kept forever[1],
- does it mean that the display state is kept when leaving the display, or
- does it mean that the display state is kept while looking at another view?

This shows that persistency and transience is two opposites in the time dimension. Therefore, we might understand these terms to mean that people use parts of the interface for a longer or shorter time than other interface parts. With this understanding, we might consider if this relate to abundant display space.

In having access to a larger area, I believe that people 'naturally' start to use more of it more persistently. For example, by using more distant areas for more persistent data and storage, which Scott et al. [124] reported as early as 2004. This also means that in providing interactions based on abundant display space, we might start to see this behaviour. I believe that toolbox views exemplifies how we may design interfaces that use abundant display space to provide more persistent views.

[1] Surely not, as a printed poster would be cheaper!

While I did not observe participants using storage areas with F3, I believe this stem from the lack of display space. For both studies of F3, I believe this was due to the limitation imposed on participants by the displays' size (84" diagonally) and resolution (3840x2160 pixels). Additionally, the time allotted for each task in the lab study did not suggest to use storage areas.

8.1.6 Movement as an implicit or explicit interaction technique

Implicit and explicit movement is relevant in relation to data analysis with abundant display space. It is relevant because people need to move to reach pertinent areas of large displays, and because people tend to move to and from large vertical working areas, such as whiteboards and large displays. Other work, which I described in section 2.1.7, have observed or studied this (e.g., [8, 9, 98, 154]).

In my work, I observed people's movement in many workshops. I described this in Chapter 4 (Paper I). It seems clear, that with abundant display space, people move away from displays to gain overview, and approach displays to see details, as we described in Paper I.

In Chapter 5 (Paper II), I described our three formative studies of movement as an explicit interaction method. In the second study, we used distance to provide semantic zoom, which participants found natural and intuitive. In the third study, we scaled visualizations to reduce the effect of distance on participants' visual perception, to the frustration of most participants. I believe this was due to people's normal use of distance to gain overview and detail, respectively.

Similarly, I reported in the deployment study of F3 in Chapter 6 (Paper III) that we moved the deployed display after four workdays, due in part to lack of use. I believe this was caused in part by to insufficient space to step back. This poses limits in terms of where to position large displays during deployments, and emphasizes one of many potential difficulties in deployment-based studies with abundant display space. I return to this concern, in discussing the methodology in section 8.2.3

While my research has shed light on physical movement with abundant display space, many opportunities still exist. The findings described in Chapter 4 (Paper I) in particular, suggests additional work. For example, I am curious of the benefits of using micro steps in interaction techniques, and imagine that it would be beneficial to let user interface widgets follow people while using abundant display space to make sense of data. For example, I imagine that a legend describing multiple visualization views could follow people, while they move between different views. Here, the legend would show relations to nearby views by using links to views' data points. Similarly, while Paper II, study 2 showed benefits of distance based semantic zoom, I believe that our study barely scratched the surface of the possibilities in this area. Lastly, I have not considered movement and collaborative visualization, which is obvious future work.

Applying the proxemics interaction framework

Mapping proxemics interaction to information visualization tasks helps to design new possibilities for interacting with visualizations. I discuss such mappings based on the studies described in Chapter 5 (Paper II). In the studies, we explored the potentials of mapping proxemics interactions to information visualizations on a large display. While the mapping brought value in proposing new opportunities for interacting with visualizations on large displays, I believe that it is clear that the structured approach to the mapping was difficult due to the definition of proxemics interaction. I outline three aspects of Halls' [58] notion of proxemics and the proxemics interaction framework that mapped poorly to our context.

First, the proxemics interaction framework only considers body posture. In our studies, we used both body and head orientation. Likewise, leaning considered as separate information can provide additional means of interaction.

Second, the framework considers relations between people and objects (i.e., Identity). In our studies, there was only one person (study participant) and one object (large display).

Third, the concept of movement is different to how we considered it. Hall relates movement to social behaviour. Here, it suggests that movement close to other people carry social meaning. For example, it may carry different meaning to move quickly or slowly past another person. Likewise, many people consider quick arm movements rude, while being close to other people[2]. The proxemics interaction framework considers movement as changes in distance and orientation over time, for example to consider "how a person is approaching a particular device or object" [9]. This corresponds well to the social examples above. In our interpretation, movement corresponded to temporary movement while not changing distance, as used in design #1.

With these concerns, it might be relevant to consider alternatives, which I believe might be more productive, and which use proxemics interaction as inspiration. First, we should divide body posture and head orientation. Second, the concepts of distance, acceleration of distance, orientation, and acceleration of orientation provides a more structured approach to exploration of movement. For these, we might then define zones that relate to Halls' notion of proxemics. Third, proxemics interaction's location and identity definitions provide little value in considering one individual's interactions in front of one large display. Fourth, if a display shows many views, then it might not make sense to consider it as one object. In this case, we might consider views as individual objects, for which people have proxemics relations.

I believe that there are many additional opportunities for exploring the space of information visualization and proxemics interaction. While we suggested many combinations, I believe that we barely scratched the surface of the opportunities. Particularly, I believe that the combinations of many small views on a large display could be an interesting area of further studies.

[2] Remember this the next time a child moves a Lego brick two inches from your eyes to show it to you. Note that the child has not yet learned that such behaviour is considered rude.

8.1.7 Open issues

I want to discuss a few observations that I did not study further. These concern touching data, pointing to data, the size of gestures, and user experience. I do this in the following.

Touching and pointing

Interacting with visualizations using touch on large displays affords new ways of interacting. Dwyer et al. [38] observed study participants to *"think with their hands"*. In a workshop in the study described in Chapter 4 (Paper I), a participant concerned with analysing website visitor statistics, held onto data on a printed sheet, while taking half a step backwards to look at other parts of the display. We also observed this behaviour in the formative lab study described in Chapter 6 (Paper III). Here, many participants held onto data bars while thinking about how to proceed with the analysis. We did not count the exact number, but estimated that it occurred in almost all study sessions. To be able to design accordingly, I believe it is important to understand when and why people touch interactive displays, not to interact, but to think with their hands. More importantly, touching data seems to occur frequently.

Similarly, people point to parts of displays. This was particularly evident in the proxemics studies, where participants experienced frustration in pointing towards display locations while approaching them. In these studies, this behaviour caused the location to diminish before participants' eyes, which led to the observed frustration.

While these considerations apply for various sizes of displays, I believe their importance increase with display size. First, I observed participants hold onto data while looking at other parts of the display, to hold onto a thought while temporarily shifting focus. I believe the increase in display size results in the possibility of larger focus shifts. Second, while pointing and walking towards small displays occur, these displays rarely move autonomously. Additionally, people potentially point more when collaborating than when working independently. Therefore, pointing should perhaps not disrupt interactions with content on large displays.

Designing interaction techniques in ways that does not interfere with these issues is an open issue, which future work might be able to address.

Large gestures

We observed a group of surprisingly large touch interactions (i.e., about six meters) in the workshop study described in Chapter 4 (Paper I). While other researchers have studied the size of gestures recently (e.g., [94, 150]), I do not know of any work that has looked at this with systematic approaches for large displays and large gestures. Simple questions in this regard, might be whether gestures' size carry meaning and which gesture sizes are acceptable.

User experience

Many participants in both studies of F3 described in Chapter 6 expressed their subjective experience with F3. What I found most interesting was that participants expressed polarised experiences. They were either very positive or very negative about their experience in using it. For example, some participants said that it was "*fun to use*" or that it "*felt fast*". In contrast, another participant articulated that a "*lack of appetite*" for using it more. I believe there are reasons for participants' statements, and that future work might be able to quantify these.

8.1.7 Summary

In this section, I discussed the most important findings in my PhD research. I summarise the most important discussion points below.

I discussed the division of space between few large visualizations and many small visualization views, and argued that the general use of spatial encoding with abundant display space is a choice between a fixed and a flexible layout. In one extreme, the layout might primarily be chosen by designers with the use of fixed spatial layouts. At the other extreme, designers might subdivide the spatial layout into views, and let users arrange these to make sense of data. The degree to which spatial arrangements are left to users, is obviously an important design choice, and depends on the goals of a specific design.

Based on my focus on letting users arrange views in most of my thesis, I discussed matters concerning meta-view interactions, visualizations, and the associated meta-tasks that emerge with this choice. An important understanding from this is that considering matters beyond individual views, allows us to shift focus from what is shown in individual views. For example, with regards to the design of F3, the bar charts shown in F3's views could easily be replaced by scatterplots. In fact, F3's View Matrix Creation technique would be more sensible for scatterplots, by essentially allowing users to manually create scatterplot matrices. To this end, I suggested a set of specific techniques in which abundant display space might be used to analyse data. In addition, I outlined the many possibilities for considering interaction with many views, and visualizations of relations between many views.

I believe that it is clear that we lack proper typologies for describing the tasks that users perform with multiple-view systems. On one side, we have incredibly detailed frameworks that should be able to express the different levels of user intents, tasks, and interactions [21]. On the other side, the definitions we use to talk about tasks in such frameworks are relatively fluffy. For example, Brehmer and Munzner define *Derive* as creating persistent data (as I described previously). However, persistency (as I also discussed previously) is relative to the context of use. This exemplifies our poor use of words to describe time, but we are perhaps equally bad at describing space (look no further than to the subtitle of the present thesis to consider the meaning of *large* in large displays). From this discussion, I argue that being able to understand, describe, and discuss matters related to time and space continues to be a major challenge in HCI and InfoVis.

Next, I discuss the choice of methodology.

8.2 Methodology

In this section, I discuss the methodology used in my PhD research. The aim of this is to compare and contrast the used methodology, and to discuss potential alternatives.

I have based my PhD studies on qualitative methodology. This follows a recent trend in information visualization research (e.g., [26, 71, 72, 88]). The research questions, which I described in Part II of the present thesis, dictated the choice of methodology. The thesis' overall research question asks how abundant display space *may* support data analysis with visualizations. Here, I used "*may*" to convey that my aim was to explore and understand a range of possibilities.

To answer this question, I conducted studies with diverse participants that looked at technologies in a range of fidelities, maturities, and complexities, in a range of different contexts, to give a broad range of answers to this question. I was more interested in understanding the possibilities of variations, than in finding the best possibility. I discuss the choices of methodology in the following, from these four aspects:

- Degree of technical fidelity, maturity, and complexity of study objects. This draws on HCI method traditions in lo-fi (e.g., [113]) and paper prototyping (e.g., [136]).
- Choice of study participants. This concerns practicalities of collaborating with domain experts, what we may learn by studying domain experts (e.g., [82, 83, 156]), and the concept of theoretical sampling in Grounded Theory [139].
- Study context. This relates to arguments for deployment-based studies (e.g., [131]).
- Analytical tools. This primarily relates to my use of Grounded Theory [139].

These aspects are summarised in Table 8.1 on page 131.

8.2.1 Degree of technical fidelity, maturity, and complexity of study object

I have based my studies on a range of technologies, from non-interactive plain whiteboards (Chapter 4, Paper I), over design scenes for interactive whiteboards (Chapter 7, Paper IV) and lab prototypes supporting a limited range of functionality (Chapter 5, Paper II), and finally, to working deployable prototypes (Chapter 6, Paper III). These different approaches obviously provided different advantages.

The simple technologies gave room for involving participants from many different domains, and allowed them to provide their own designs and interpretations, similar to the benefits of paper prototyping [136]. This is similar to related work (e.g., [156]). These approaches resulted in a broad range of valuable findings, but they also introduced problems. In the study described in Chapter 4 (Paper I), the use of whiteboards failed to provide participants with any sense of spatial resolution (as we discussed in the paper). In contrast, many participants had a much better sense of the temporal resolution in the imagined interaction designs. I also observed these issues in the study described in Chapter 7 (Paper IV). Here, some participants were much more likely to consider interaction, than static visualizations. I believe this exemplified the difficulty of sketching with high spatial resolution. In both these studies, many participants used verbal explanations to manage these issues. This shows the importance of analysing the verbal protocol in both of these studies, and to link the verbal and visual empirical data.

The study described in Chapter 4 relied much on participants' data, tasks, and knowledge of technology. Thus, existing technology was an important inspiration for many participants, and might have biased the participants towards for example the representations used in their domains. In comparison, the study described in Chapter 7 used related work of representing view relations as inspiration for the design scenes. This biased the study towards known visualization techniques. Although participants were concerned of the bias introduced by their prior knowledge, they identified many novel techniques, in addition to considering many known visualization techniques. Both of these studies attempted to provide participants a "clean slate" to fill. It is clear however, that any question needs to be rooted in some common understanding to be productive. For example, to counter bias, half of the participants in the view relations study sketched view relations before we showed them examples of our designs. This was difficult with little prior introduction to view relations, which resulted in few insights from the sketching in these sessions. On the other hand, the relations shown in the seven design scenes enabled participants to comment on the designs, and to use them as inspiration for many novel ideas. Walny et al. [157] also used near-interactive research prototypes to study interaction and reported limitations that are comparable to the studies in Chapter 4 and 7.

The more developed prototypes enabled me to evaluate designs in use. This allowed me to understand the use of large displays to conduct analyses, and to understand the designs' potentials. We systematically controlled the interface alternatives in the studies described in Chapter 5 (Paper II). This allowed participants to compare the alternatives to each other as recommended by Tohidi et al. [144], and helped us to elicit qualitative interview data from the participants, as we varied the interfaces. I described F3 and the studies of F3, in Chapter 6 (Paper III). For these studies, participants were free to conduct their analyses using any of the various interaction techniques provided by F3. This made it possible to observe which techniques participants favoured and how they used the techniques. This for example, enabled us to identify the use of toolbox views. Additionally, the working deployable prototype enabled the participants and us to understand the value of F3 in the context of analysis work, which we used as basis for the interviews.

8.2.2 Choice of study participants

In my PhD research, I have had the pleasure of interacting with and observing participants from a broad range of backgrounds. In an attempt to group these many participants, I identify them as

- analysts or domain experts,
- visualisation or interaction experts, or
- 'average' people that held a University degree and have some experience with data analysis (in the broadest definition – see Chapter 1).

I discuss the roles of the first two groups in my work below.

Domain experts

I based the studies described in Chapter 4 (Paper I) and Chapter 6 (Paper III) on a range of methodologies that involved domain experts. Here a domain expert means a person that has expertise in a work domain. I focused on data analysis. Therefore, I interacted with domain experts for which data analysis tasks were important in their work domain.

The first study involved domain experts from many domains. This is comparable to the goals of Kandel et al. [82], Walny et al. [156], and Kandogan et al. [83]. This approach enabled me to obtain insights that were reflected in a range of domains, and which is thus applicable for many different analysis contexts in which large displays might be useful. Based partly on these insights, I designed and implemented F3, as a working prototype, which I evaluated in one of the domains that I based the workshop study on. Additionally, several participants in the formative studies of F3 considered using the system within their work domain. This suggests the usefulness of the interaction techniques for other domains, which I believe is partly due to the broad foundation of the workshop study.

We aimed to provide generalizable findings from the workshop study. This follows a common thread in Grounded Theory, which aims to describe commonalities and variations across fields [139]. This aim stands in contrast to studying domain experts, where the goal is to understand domain experts' specific context, tasks, and data. However, the findings of the workshop study showed that many aspects of analysis occur within very different domains. In my opinion, grounding the findings in concrete domains thus helped to base the very abstract imagination of a large interactive display, in concrete work. The different domains provided insights that is not specific to one domain, but is transferable across domains. The results of the formative study of F3 also suggested this.

Much of the work in designing and evaluating F3 thus included domain experts. This helped to keep the work grounded in a domain. However, aside from the resources needed to interact with domain experts, there were aspects of these collaborations that were difficult to manage.

First, our interest with F3 was to focus on the meta-view interactions. However, the domain experts suggested many ideas that would shift the focus. For example, they frequently suggested integration to other systems. While these suggestions showed the limits of the deployment study, they were outside the scope of F3. This problem illustrates the different set of goals our collaborators and we as researchers had, and emphasises the necessity of aligning expectations between collaborators.

Second, the complexity, scale, and sensitivity of the domain experts' data was high. This resulted in two primary barriers: (1) identifying parts of their data and analysis tasks, which we could support with tools; (2) managing their data on a technical level, while providing interactive query responses to data sources that required very limited access to the data to a select few designers and programmers. While we handled the first barrier through observations, interviews, workshops, and Contextual Inquiry [15], we handled the second barrier mainly with existing data management technologies and formal agreements with the Danish Data Protection Agency.

Sedlmair et al [126] have described similar issues in involving domain experts in deployment studies. I return to this in the next subsection.

Visualization and interaction experts

I based the studies described in Chapter 7 (Paper IV) on visualization and interaction expert participants. In our paper, we argued that using visualization experts as study participants was the most sensible solution. We based this line of argumentation on the consideration that our aim was to study meta-data relations which concern abstract visualization tasks, and that this group of participants therefore would fit better and be able to provide more relevant insights, than domain experts.

I believe that it was valuable to include these participants and think that they provided many fruitful considerations. For example, it was clear that many of the participants had a strong knowledge of the field of visualization techniques and their potential pitfalls. Similarly, it was clear that many used their knowledge of the existing body of research, which might have limited their imagination. Therefore, I believe that it would be interesting to invite domain experts to a similar study, to gain insights that are more grounded in analysis work, and to better understand the differences between these groups of participants. I would be curious to see the findings of such a study.

Choosing participants

The choice of participants in any study is important. Above, I discussed the choices I took in my respective studies. Strauss & Corbin [139] argue for using theoretical sampling to "maximize opportunities to discover variations among concepts and to densify categories in terms of their properties and dimensions."

In the workshop study described in Chapter 4 (Paper I), we sampled participants from diverse domains and different types of data analysis to maximize variation and to attempt generalization. This is an example of theoretical sampling. Here, we chose to focus on diversifying participants' domains, while only sampling participants from the set of people that conduct data analyses. In the relations study described in Chapter 7 (Paper IV), we chose to focus on visualization and interaction experts. As I discussed above, an interesting next step could be to expand the theoretical sampling in the relations study, by conducting similar sessions with domain experts.

8.2.3 Study context

I have conducted observational studies in and out of participants' context of work. In all four papers described in Part II, we studied participants out of their context (i.e., in labs). This approach is common both in HCI and InfoVis, and so also in the work I described in Chapter 2 (e.g., [4, 8, 36, 38, 69, 76]). In Chapter 6, I described a study that I conducted in participants' work domain (this is called for by e.g. Shneiderman & Plaisant [131]). I discuss the relative benefits of these alternatives in the following, based mainly on the studies of F3, which I described in Chapter 6 (Paper III).

To understand the work domain of the analysts for which we designed F3, I conducted semi-structured interviews and contextual interviews at their workplace, in addition to observing them work. This approach to studying them was decided from a practical point of view. However, in retrospect, for novices, it is not recommended to mix observations and contextual interviews. I found that it was difficult to make the analyst set aside time for contextual interviews, knowing that I would be around the office during an entire week. I suspect that setting up a few hours with each analyst for interviewing them in context might have created a better mutual understanding of the aim of the interviews.

We also conducted workshops with the analysts. For example, they participated in the workshop study described in Chapter 4 (Paper I). They also participated in design workshops where we presented mock-ups to the analysts and sketched designs together with them.

To evaluate F3, we conducted both the lab study and the deployment study. In the lab study, we asked participants with no background in the analysts' domain, to work with simple tasks derived from the domain. In the deployment study, we asked the analysts to use F3 as part of their work for two weeks. Aside from the studies, having access to the analysts' data helped us to gain an overview of the data, and understand some of its complexity. Brief email and face-to-face conversations supported this process.

The alternative studies in and out of the domain and context of work brought independent value and complemented each other nicely.

First, while we were able to obtain many insights from observations and interviews in context, the workshops helped to align our understanding of the analysts' issues and requirements with them. Thus, in addition to improving the designs and obtaining new ideas, they worked as a sanity check before further design and implementation.

Second, the initial lab studies (described in rows 4 and 5 in Table 6.1) were crucial in understanding the importance of views' relations. While we could have observed these problems in the later deployment study, this would have been a waste of resources. Furthermore, the relation representations became a fundamental part of F3's design, which helps to convey the context and analysis of the visualizations shown in each individual view.

Third, the lab study (described in row 6 in Table 6.1) gave us the opportunity to see many participants work with the same set of tasks, and understand the difficulties that participants experienced. For example, the study showed the issues of drilling deeper into the data than necessary and the inconsistent possibilities for combining interface elements. We also found aspects of F3's designs that caused problems in the lab study, which seemed less problematic in the deployment study.

Fourth, the deployment study allowed us to observe the analysts use F3, and to interview them about using it for their analysis tasks. In the following, I discuss the challenges of the deployment study in more detail.

Challenges in deployment

In the deployment study that I described in Chapter 6 (Paper III), we deployed F3 for two weeks with the group of domain experts that F3's design was based on. In the course of deployment, we identified many issues, fixed some of them, and changed the underlying data per requests from the domain experts. We visited the site each day for one to six hours, to solve technical issues, to answer questions, and to motivate, interview, and observe the domain experts using F3. However, we saw limited use of F3. I believe there were two main reasons for this:

(1) Lack of integration with other systems. This was a technical issue. F3 did not enable participants to start an analysis in front of the large display, and continue it when returning to their desk. Similarly, F3 did not enable the analysts to transition from their work desks to the large display. This resulted in F3 being isolated from the rest of their tasks, and thus only useful for brief exploratory data analysis. Sedlmair et al. [126] noted similar problems in integrating research prototypes in deployment studies.

(2) Duration of deployment. Due to the relatively short study duration, the participants lacked time to get to know the system, and to start using it as part of their analysis tasks. This also resulted in few situations were F3 would be beneficial for the analysts. While deployment studies are suggested to last from several weeks to months [131], I believe that the two weeks duration was too short.
In addition, it would have been interesting to install the display in a meeting room. However, because employees also book meeting rooms for non-analysis meetings, this would have resulted in even less use of F3 during the deployment period.

Clearly, to conduct a longer deployment study, we would need to address the first point[3]. However, integrating F3 with the analysts' other systems would require an extensive effort, even if access to a modified version of F3 from the analysts' desks had been sufficient.

I believe that our choice of conducting a limited deployment study provided valuable insights compared to the expended resources. During the two weeks, the analysts were able to use F3 in the context for which we designed it. Most importantly, the deployment allowed us to: (1) observe the analysts use the system and explain its use to others, and (2) obtain valuable insights from interviewing them about how they thought F3 supported their analysis tasks. I believe the analysts we interviewed had a high degree of ability to imagine using F3, because they had used it in the two-week

[3] To conduct a longer duration deployment, we would also need to improve stability to reduce the need for daily visits.

period leading up to the interviews. This supported the interviews and ensured the high quality of insights that we were able to gather from them.

Obviously, given only two weeks, we could not provide quantitative insights into which interaction techniques the analysts used and for what. A longer deployment period would have enabled decreasing visits to the site, analysts to gain expertise with F3, and log data to provide useful insights on patterns of use. I believe this could be an interesting study and expect that future work will study data analysis on large displays over a longer period.

8.2.4 Analytical tools

To analyse the empirical data that I collected as part of my PhD work, I have used Grounded Theory based approaches, the Instant Data Analysis [84] technique, and more ad hoc approaches for less structured parts of analysis. This follows analysis approaches in related work (e.g., [26, 71, 127, 156, 157]). In the following, I focus on my use of Grounded Theory.

Grounded Theory advocates letting the data "speak for itself". The analyst uses the raw collected empirical data to build analyses. Then, the analyst identifies concepts through open coding, in an iterative process, and identify important concepts as categories. As the analysis progresses, the analyst identifies properties of categories, relationships between them, and organises these according to dimensions. To describe variations of a dimension, the analyst uses axial coding. In any of these processes, analysts may use theoretical sampling to fill holes in the empirical data. This process is resource-intense. Sedlmair et al. [127] have questioned the value in this process, and argues for learning just enough to abstract, rather than attempting to understand all details.

I discuss the use of Grounded Theory in my work, which I believe is particularly relevant to discuss for several reasons. I publish in areas of HCI and Information Visualization. Although it is accepted to use qualitative methodology in the outlined research areas (e.g., [26, 71]), many researchers use quantitative approaches. Here, the studies focus on: (1) technical contributions, (2) establishing hypotheses, (3) conducting controlled experiments that compare time and error based measures (dependent variables) for different conditions (independent variables), and (4) subsequent statistical analysis. Therefore, they have limited understanding, knowledge and experience with qualitative methodology. Moreover, the technical contributions in the fields provide a level and focus of reproducibility that is difficult or impossible to provide with qualitative methods. Qualitative analysis, and thus Grounded Theory is very different from this. It has less focus on reproducibility, control of studied object, and generalizability. Instead, Grounded Theory focuses more on understanding variations and relationships between phenomena.

The lack of knowledge of qualitative methodology may result in limited apprehension of results based on these. First, this requires a strong argument for using Grounded Theory and second, a sufficiently detailed description of the analysis methodology and process when reporting in the research areas. Next, I discuss two important considerations in relation to this: (1) Analysis process and (2) theoretical sampling and saturation.

Analysis process

When we described the findings of the relations study in Paper IV, which I described in Chapter 7, my goal was to give a clear description of the process we went through from raw data to the presented framework.

This is in contrast to Grounded Theory, in which it is acceptable to state the used analysis approach, potentially by outlining the phases of said analysis. This does not map well to quantitative methodology, where it is easier to follow the process from raw data, to results, to discussion. Therefore, I believe that it is important to provide a thorough account of the employed methodology in disseminating results of such studies in HCI and Information Visualization. In Paper IV, we first described the study and analysis methodology. We then described the concepts that arose from the data. Subsequently, we described how the concepts mapped to dimensions of the framework. Finally, we described the framework and its dimensions based on the results of the study, and related work.

I believe this approach has value, when disseminating the results of such analyses to more technical readers. Further, I believe this approach has value in attempting to bridge the gap between qualitative and quantitative methodology, which both offer many benefits. However, other contributions that use Grounded Theory do not follow this approach (e.g., [156]).

Theoretical sampling and saturation

I conducted two studies in which I employed Grounded Theory in a lab context. The workshop study and the view relations study, which I described in Chapter 4 and 7 (Paper I and IV).

In the workshop study, we first conducted two workshops and analysed these. We then conducted the remaining nine workshops. Finally, we analysed the collected video data from all workshops. In the relations study, we conducted all ten sessions and subsequently analysed the collected video data.

This stands in contrast to Grounded Theory, which advocates theoretical sampling and saturation. Theoretical sampling suggests finding and collecting data to fill missing ranges in e.g., a dimension. Theoretical saturation suggests continuing to collect and analyse data until the theory is saturated. Saturation occurs when no new or relevant data emerge and categories are well developed in terms of its properties, dimensions, and relationships. Strauss & Corbin argues that, “Unless a researcher gathers data until all categories are saturated, the theory will be unevenly developed and lacking density and precision.”

Above, I first described how the lab studies used a Grounded Theory based approach. Secondly, I described how Grounded Theory stands in contrast to this. The limitations set out by conducting lab studies naturally dictate how we conducted the studies. For example, we asked participants in the relation study to look at the scenes that we designed. Here, the scenes were an attempt to provide variation. Additionally, resource constraints also set limitations. For example, it would require lab access for a longer time-period to analyse data after each session, compared to conducting all sessions before starting analysis.

Alternatively, we could have studied the research questions outside the lab. For example, I considered interviewing individual participants at their workplace. I would ask to interview participants near their desk, in front of a whiteboard. Instead of relying on interactive displays, I could sketch the relation scenes by hand, and base the interviews on this. A similar approach was used by Walny et al. [156]. We chose to base the study on the interactivity and resolution afforded by the large display. However, I imagine that the study setup outlined above could provide important insights. Additionally, this would allow me to better analyse data between interviews, supporting theoretical saturation, and thus facilitate a study that is more in line with Grounded Theory.

An alternative point of view is to consider what each of the studies provided in terms of understanding abundant display space. For example, it might be appropriate to consider the expertise of participants in the relations study on a dimension of visualization expertise. All the participants in the study were skilled. Conducting a similar study with domain experts as suggested in section 8.2.2, would reveal new insights and be comparable to the notion of theoretical sampling. In this light, the years of analysis that goes in to conducting Grounded Theory (e.g., [127]) might appear more sensible.

8.2.5 Summary

In this section, I discussed the most important methodology considerations from my PhD research.

First, I discussed the degree of technical fidelity, maturity, and complexity of study object, and discussed the benefits and disadvantages of using lo-fi prototypes versus more interactive and refined prototypes. While lo-fi prototypes allowed us to study visualizations on large displays without writing a single line of program code, they worked poorly to convey a sense of spatial resolution, colour resolution, and interaction. On the other hand, highly interactive prototypes come with their own set of drawbacks. There are slow to develop, and inflexible when study participants suggest a new approach to interacting with or visualizing data. I believe the employed methods have served to shed light on the appropriate research questions, and have complimented each other well.

Next, I discussed the participants that I invited to participate in my studies, and ties together with the previous considerations of lo-fi versus hi-fi prototypes. It is typically impossible to create hi-fi prototypes that fit all domains. Thus, the choice of using lo-fi prototypes helped to obtain generalizable insights. I also discussed the theoretical foundations of sampling participants from diverse domains and practicalities of how to work collaborate with domain experts. Again, I believe my choices of participants in the different studies worked well. It might be debatable whether inviting visualization and interaction design experts to the study on view relations really proved to be useful. I believe some aspects of this study is reminding of expert reviews, but without the usual heuristics, which did not exist for view relation representations. Rather, the results of the study are somewhat similar to heuristics. Thus, it might be argued that the visualization and interaction design experts helped to define a set of heuristics for view relations – which we described as a framework.

Third, I discussed the study context. I believe the important part of this discussion, is the extent to which the deployment study was successful. Due to time constraints and maturity of F3, the system was only deployed for two weeks. This also meant that we did not get to see much use of the system that was not initiated in some way or another by us, and consequently, that the log analyses that we initially intended to conduct was of limited value. This most of all shows the efforts that goes into conducting a deployment study based on novel technologies. Rather than sending the participants in the deployment study an .exe file to run, we had to order a shipment of an 84” display. Aside from the limited insights we obtained from seeing the system in daily use, I believe that the physical presence of the display at the analysts’ office helped them to consider their use of it, in the context of their work. Wrapping up, to conduct a proper, long-term study of F3, the system would need to be more mature and more tightly integrated into the current work practices and systems at the deployment site. However, such integrations might to some extent be handled by simple screenshot-based solutions, that would allow the analysts to remember their findings from analyses conducted with F3.

Finally, I discussed the use of Grounded Theory [139], primarily in terms of the analysis process, theoretical sampling and saturation of empirical knowledge. I discussed how HCI studies are often conducted in labs and are based on a pre-decided number of lab sessions, and how this is contradictory to Grounded Theory. Finally, I compared the many smaller studies that we often perform in HCI and InfoVis, to the tradition of longer studies in social sciences, in which Grounded Theory is rooted. This comparison suggests that perhaps the many smaller studies might be considered to be different angles and theoretical samples of a bigger picture.

With this, I have briefly summarised the different methodological choices, which are also shown in Table 8.1 on page 131. In the next chapter, I conclude this PhD thesis.

	Paper	Aim	Method	Collected data	Analysis	Medium	Participants
Chapter 4	I	Elicit tasks	Interviews	23 task descriptions & 452 sheets of data printed on A4 paper sheets	Ad	-	D
	I	Explore large displays Info-Vis in many domains	Workshops	17 hours of video	GT	D W	D
Chapter 5	II	Evaluate design #1	Formative evaluation	Observation notes & memory	IDA	L B	N
	II	Evaluate design #2	Formative evaluation	Observation notes & memory	IDA	L B	N
	II	Evaluate design #3	Formative evaluation	Observation notes & memory	IDA	L B	N
Chapter 6	III	Understand domain	Observation and contextual interviews	Notes, audio capture, photos, domain documents, data extractions, …	Ad	C	~ D
	III	Design	Sketching workshops	sketches, photos, and notes	Ad	-	D
	III	Design	Evaluating mock-ups	Notes	Ad	L T	~ D
	III	Evaluate conceptual model	Formative evaluations	Observation notes	Ad	L T	N
	III	Evaluate conceptual model	Formative evaluations	Observation notes	Ad	L T	D
	III	Lab study	Formative evaluations	Observation notes	IDA	L T	N
	III	Deployment study	Observations	Observation notes and audio capture	Af	L T	~ D
	III	Deployment study	Usage logging	Logs of use	Ph	L T	~ D
	III	Deployment study	Semi-structured interviews with access to studied system	Observation notes and audio capture	Af	L T	D
Chapter 7	IV	Explore and evaluate view relation representations	Expert evaluation and design (sketching)	70 sketches 15 hours of video	GT	L T P	V

Ph: Post-hoc data analysis
Af: Affinity diagramming
IDA: Instant Data Analysis
GT: Grounded Theory
Ad: Ad hoc

B: Body tracking
P: Pen
T: Touch
L: Large display
W: Whiteboard
D: Data in print
C: Context of work

V: Visualization experts
N: No requirements
D: Domain experts

Table 8.1: Overview of the methodological activities in my PhD work.

Chapter 9
Conclusion

In this thesis, I have sought to answer how abundant display space might support visualization-based data analysis. I presented this research question in Part I, and answered it through four paper contributions. First, I presented these separately in Part II. Then, I synthesized the individual papers' results and discussed them together in the previous chapter.

I outlined specific questions that related work had not answered towards the conclusion of Part I. For example, I inquired: 1) how might abundant display space support exploration of large data sets, and 2) how might we tailor interaction techniques to abundant display space, and thus leverage the benefits they provide.

With abundant display space, visualization designers have two options. I described and discussed these in the previous chapter. First, they can use the available space to fill a display with one large visualization. This gives room to subdivide the space based on composite visualization techniques. Alternatively, they can display many smaller visualization views, which allow users to arrange these to make sense of data. My focus has been on the second option. In choosing this option, there are two foci: considering visualization and interaction techniques within *or* between visualization views. In my research, I have identified the importance of between-view interaction *and* visualization. With this, I have defined a large design space. For example, we might consider interaction techniques that allow people to drag visualization views together to combine them, and how we might show relations between them. I have shown several of these possibilities in my research.

I have contributed specific interaction techniques that facilitate comparisons between and within views based on juxtaposition, and that allow people to construct analysis trails and to branch analyses. These possibilities show how abundant display space might be used to reason about alternatives, and facilitate data exploration and hypothesis testing.

The contributed techniques present a set of specific techniques that use abundant display space to support visualization-based data analysis, and is thus one approach to answer these questions. With this approach, I believe I shed new light on how abundant display space might support data analysis.

In basing many of my studies on qualitative methods, the results show potential approaches to enable data analysis and designing visualization tools. Some of these results mainly take the form of what could be described as existence proofs. For example, the framework described in Chapter 7 describes a range of relations between visualization views. While I am confident these different relations exist, we are not sure that these encompass all relations that might exist. My methodological choices also imply that I have not quantified the benefits of these, for example in terms of analysis speed or quality of insights.

The results presented in this thesis thus show that with abundant display space, analysts are able to analyse large data sets. However, I am not confident that the abundant display space has any impact on the size or volume of data that can be analysed or explored. And my empirical work does in no way either suggest or quantify if this should be the case. However, I do believe that the level of data complexity might be more easily handled with abundant display space, for example by allowing different views to show different facets of data sets. While this is my opinion, the empirical work offers few indications of this. What I did see, was that the domain analysts who used F3 seemed comfortable analysing much more complex data than what they were used to with their desktops displays, SAS, and Microsoft Excel. I believe this observation might be due to the large working area and the interaction techniques provided by F3.

In designing F3, we intended to show process and interaction relations. These view relation representations seemed to aid analysts in understanding the relations between views, to compare and reason about alternatives, and to test hypotheses. I believe that the techniques did support this, but our observations only vaguely show this. Additionally, other factors might explain our observations.

While I have only partly answered how abundant display space might be used to reason about alternatives and test hypotheses, we were certainly able to show with F3, that it is possible to design interaction techniques that support analysts in exploring data using abundant display space. So much in fact, that we in some occasions observed over-exploration or as we called it, *drilling too deep*.

Additionally, our studies have shown that we can create interaction techniques which are tailored to situations where display space is abundant. It is debatable at which size and spatial resolution we can confidently argue that space is abundant. While the deployment studies evaluated F3 on an 84” display at a spatial resolution of 3840x2160 pixels, the actual design of F3 were conducted on a somewhat larger 130” display at a spatial resolution of 7680x3240 pixels. Some of F3’s interaction techniques seemed slightly limited on the 84” display. For example, the View Exploding technique took up most of the width of the 84” display (see Figure 6.11).

Finally, I have shown how we might provide view relation techniques. I believe an obvious next step is to consider how we might provide interaction techniques for the view relation representations as well. Finally, I believe view relation techniques should be considered in all visualization designs that involve abundant display space – even if the design does not allow users to lay out view by themselves.

While I have suggested many view interaction and representation techniques, it is clear that many additional and promising possibilities exist, for both between-view interaction *and* visualization. In the next section, I outline potential future work.

9.1 Future work

While this thesis has provided a range of important results regarding the potentials of using abundant display space for data analysis, many questions remain open. In the following, I briefly discuss future perspectives of my research and outline opportunities and challenges in two aspects of my work. First, I believe that I have merely scratched the surface of the potential benefits of meta-view interactions and visualizations. Secondly, I believe that it is interesting to explore the concept of touch thinking.

9.1.2 Meta-view interactions and visualizations

I described and discussed the framework of view relations in Chapter 7 and 8. I believe that I merely scratched the surface of the potential possibilities and benefits of meta-view interactions and visualizations, and see many interesting avenues of further work in this area.

First, formalizations for understanding, comparing, and choosing between view relation techniques are missing. Such formalizations would be created based on the view relations framework, and would bridge the gap between visualization tasks (e.g., [21, 61]), visual variables (e.g., [14, 25]), multiple coordinated view systems (e.g., [7, 114]), the InfoVis pipeline (e.g., [25, 27]), formalizations of visualizations (e.g., [151]), and existing multiple view systems (for example, the systems described in Chapter 7). This would help to create a repository of tasks related to representing view relations, to generate new view relation techniques, and to evaluate existing techniques.

Second, while many techniques for showing and interacting with view relations exist, the framework shows a large potential for novel techniques. For example, few contributed techniques show encoding relations or use meta-data components to represent relations. Additionally, qualitative and quantitative studies of view relation representation techniques are rare [55], and the few existing evaluations focus on single techniques (e.g., [37, 143]). This also includes my work on F3. To address these challenges, it would be interesting to design, implement and evaluate novel view relation representations. These could be designed both for wall-, desktop-, and mobile-sized displays, and consider aspects of interaction, collaboration, and transitioning between multiple devices. In addition, empirical lab- and deployment-based studies of such designs could provide interesting insights. With inspiration from Griffin and Robinson [55], such studies might compare alternative view relation techniques, in comparative lab-based experiments that quantify speed and quality of analyses, or alternatively in comparative studies that seek to quantify analysts' insights.

I believe such efforts would improve the available analytic tools and thus enable cross-disciplinary teams to collaborate on large data collections, more efficiently and with increased quality of analytic output.

9.1.1 Touch-thinking

I observed the touch-thinking phenomenon in the studies described in Chapter 4 and 6 (Paper I and III). Participants held on to data points while looking at other parts of the display, seemingly while attempting to understand the visualised data, or deciding their next action. Dwyer et al. [38] and Jansen et al. [78] reported similar observations.

I believe that reaching a deeper understanding of this phenomenon presents an exciting avenue of future work and presents a current challenge in InfoVis and HCI. Understanding this phenomenon could potentially enable us to design more effective interaction techniques that would increase peoples' ability to use their hands to think. This is in contrast to many current techniques that react instantly to any touch input, and thus do not enable people to touch arbitrary parts of an interface without affecting the system state.

I believe that studying touch-thinking experimentally is an interesting research opportunity. To obtain inspiration for designing such an experiment, I would collect the many sources of empirical evidence for this phenomenon and study them informally. This would allow me to understand the varied types of touch-thinking, which could be used to design good tasks for one or more experiments. These experiments would quantify the effects of touch-thinking based on quantitative measures. In such an experiment, I would ask participants to perform a range of cognitive tasks with a touch interface. For example, to solve a puzzle or manually lay out nodes in a graph, as in Dwyer et al. [38]. In the experiment, I might first attempt to establish a baseline of participants' use of touch-thinking, to observe the extent to which they "naturally" think with their hands. Next, the study would follow a within-subjects study design, with touch-thinking as an independent variable. One potential method to control this could be to lock the position of pieces/nodes with long-pressure. However, more useful, effective, and less interfering techniques might exist. During the experiment, dependent variables of task time and errors would be collected to quantify the effects of touch-thinking.

This experiment will provide insights into the effects of touch-thinking, and whether the people that use touch-thinking by themselves benefit more or less from doing so. The experiment might also shed light on which tasks or levels of complexity that should be conducted using touch-thinking.

9.2 Summary

In summary, my research supplemented and complemented recent studies that aimed to support complex data analysis tasks with large displays. My studies went beyond designing for example pointing and manipulation techniques for large displays. Doing so, I extended our understanding of how to support data analysis on large displays, through participant-based design studies and evaluations, and by contributing novel interaction and visualization techniques tailored for such technologies.

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Paper I

An Exploratory Study of How Abundant Display Space May Support Data Analysis

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ABSTRACT
Large, high-resolution displays offer new opportunities for visualizing and interacting with data. However, interaction techniques for such displays mostly support window manipulation and pointing, ignoring many activities involved in data analysis. We report on 11 workshops with data analysts from various fields, including artistic photography, phone log analysis, astrophysics, and health care policy. Analysts were asked to walk through recent tasks using actual data on a large whiteboard, imagining it to be a large display. From the resulting comments and a video analysis of behavior in the workshops, we generate ideas for new interaction techniques for large displays. These ideas include supporting sequences of visualizations with backtracking and fluid exploration of alternatives; using distance to the display to change visualizations; and fixing variables and data sets on the display or relative to the user.

Author Keywords
Large high-resolution displays, interaction techniques, user study, workshop, visualization.

ACM Classification Keywords
H.5.2 [Information interfaces and presentation]: User Interfaces—Graphical user interfaces (GUI).

General Terms
Human Factors.

INTRODUCTION
Large, high-resolution displays are becoming ubiquitous, with size and resolution increasing at impressive speeds. Displays now offer sizes well over 100 megapixels [2], resolutions over 100 DPI [24], and more stable and fine-grained support for multi-touch (e.g., Microsoft Surface 2.0). Research has shown that such displays improve performance and user satisfaction [12,33].

An additional hope for large, high-resolution displays is that they support data analysis by giving “space to think” [1]. We use data analysis in a broad sense to denote gathering, organizing, reading, extracting, visualizing, checking, and narrating data; we see it related to sensemaking [26] as well as to the types of activity supported in visual analytics [35]. The contention here is that large, high-resolution displays may fundamentally change how data analysis is done by affording new opportunities for visualizing and interacting with data.

Much research has dealt with how users can interact with large displays, proposing and evaluating techniques for pointing [6], gestures [22,36], text input [29], and using physical movement as a navigation aid [2]. Such techniques are typically generic and support data analysis only indirectly by facilitating input. Less work has been done on supporting complex analysis, though some papers discuss how to support sensemaking [1] and collaboration on large displays [9]. Studies such as [1,37] have helped understand how single or multiple users benefit from large displays in analysis tasks in a particular domain. However, they rarely identify new visualization or interaction techniques for using space to think.

Although recent work has helped understand complex analysis tasks with large displays, we know little about how to support analysis beyond efficient pointing and window manipulation techniques. It is unclear how abundant display space can support data analysis tasks in general. Moreover, we lack visualization and interaction techniques that help users benefit from large displays when analyzing large amounts of data. This raises several questions: How may large displays support what-if analysis? How may abundant display space be used to reason about alternatives? Can we come up with interaction techniques that support analysts in hypotheses testing?

The present paper tries to answer these questions by taking a complementary approach to existing studies [e.g., 1]. We conduct workshops that focus on analysis activities and how they may be supported on large displays. Workshop participants redo analysis tasks from their work using a simulated large display, mocked up by whiteboards and various paper representations of data. As participants redo tasks, we probe them with questions on how to do their analysis given the large display. Workshop participants are sampled from diverse domains and different types of data analysis so as to maximize variation and to attempt generalization. We analyze video recordings of the workshops in detail using a grounded theory approach [31].

Based on this analysis, we report findings across domains and present a catalogue of ideas from the workshops.

Our aim with this work is to generate new directions for researchers and practitioners on how to design for large displays in order to make abundant display space work in analysis tasks. The paper makes three contributions:

- An analysis of 11 workshops spanning domains as different as artistic photography, phone log analysis, and health care policy.
- A set of ideas for making use of large, high-resolution displays for data analysis.
- A workshop method for working with concrete tasks using imaginary technology (in our case, a large, high-resolution display).

RELATED WORK

Much work has investigated the use of large displays both for single-person use [12] and for collaboration [18]. Early examples include iLand [32] and Liveboard [13], which focused on office work and face-to-face meetings. Large displays have been shown to improve users' performance and satisfaction in a variety of tasks [2,4,6,8,12]. Increasing display space helps view multiple windows with less navigation [12], improves task switching [3], enhances awareness of peripheral applications [8,16], gives a better peripheral view [7], and may promote physical navigation [2,41]. Even with the view as a normal-sized display, large displays may increase performance in spatial tasks [33].

The present study focuses on data analysis in a broad sense, taking the phrase to denote gathering, organizing, reading, extracting, visualizing, checking, and narrating data. This sense includes the types of activity supported in visual analytics [35] and listed in taxonomies of information visualization [40]. The focus on data analysis differs from many of the studies mentioned in the previous paragraph. They have solved usability problems in interacting with big screens, problems of reaching over a distance, and so forth, and to a lesser degree concerned analysis tasks.

In contrast, we focus on how an abundance of space by way of large, high-resolution displays may support data analysis. For instance, increasing display space may allow analysts to view more data at a time or to organize data spatially as appropriate for their work. Few empirical studies help understand these benefits for specific types of analysis. Andrews et al. [1] described how intelligence analysts benefit from large displays particularly for sensemaking, which is a common analysis activity [26]. Andrews et al. argued that a large, high-resolution display fundamentally changes analysis tasks compared to smaller display sizes.

Isenberg and colleagues [19] studied how visual representations are used in analysis. They had individuals, pairs, and triples work on data sets from SPSS; tasks comprised open discovery tasks and more focused tasks with one correct answer. From coding of videos they derived a description of the analysis process involved in solving the tasks. The conclusions with respect to interaction and visualization design, however, mostly concern the benefit of process-free tools and the drawbacks of implementing a strict structure in tools for supporting analysis. Robinson [25] report on a similar study of how pairs of experts in geography and infectious diseases synthesize collections of analysis artifacts. Robinson noted that collaboration style and organizational strategy varied between pairs even though pairs had similar backgrounds. Ziemkiewicz et al. [42] presented a case study of the use of immunobiology visualizations. They collected videos and screen captures to analyze how visualizations were used and conducted interviews with four researchers that had used the tools. Thereby Ziemkiewicz et al. identified distinct ways of using the visualization, which varied greatly among individuals.

The above work mainly concerns understanding the use of visualizations. While such work help design for visualizations, few studies have directly attempted to identify and propose new ways of interaction and new visualization techniques that work for large displays. This is the motivation for the present study, where we elicit ideas for supporting data analysis with large displays.

In addition to these considerations about large displays, we also briefly want to discuss work that relate to our choice of method. The literature shows several ways of eliciting design ideas from users when the goal is technology innovation [34,39]. The main goal of the present paper is to use workshops to elicit ideas. We draw on participatory design work on conducting workshops, in particular on the inspiration card workshops [17]. In the workshops we use whiteboards as a proxy for large, high-resolution displays. Several papers on visualization and interaction have concerned whiteboard use [10,38]. For instance, Walny et al. [38] analyzed snapshots of whiteboards, created by 69 researchers. They showed how whiteboards contained complex visualizations, using a variety of types of representations and linking. Their study provides an argument for using whiteboards to simulate large displays; next we describe how we do so in the workshops.

METHOD

The question guiding the study is: How would professionals do data analysis tasks on wall-sized interactive displays? To better understand this, we conducted workshops with 11 groups of 2 to 3 analysts from a variety of domains. We chose to conduct a workshop study because we wanted to observe real, hands-on analysis work, carried out on what participants would think of as a large interactive display. The key part of the workshop is to have participants imagine a whiteboard to be a large, high-resolution display and redo tasks on the imaginary display.

We argue that this approach offers several benefits. First, this approach is more general than individual studies of data analysis. Second, this approach is grounded in concrete data analysis tasks, rather than trying to develop general models of analysis activity and derive design implications from them. Third, this approach may offer a sweet spot between contextual studies and generalizability.

Participants

Eleven groups of professional analysts agreed to participate in the study. The groups were recruited from research and business domains confronted with a need to collect, analyze, understand, and act on large amounts of data. Table 1 provides a summary of the groups; their names replaced by the letters A through K and group size indicated as #. Participants were invited in small groups so as to facilitate discussion and to help each other make the leap of faith in simulating that the whiteboard was a large display.

Our sample comprises four (E, G, H, and I) scientific research groups that analyze large data sets. A main objective of their analysis work is to report results to scientific communities. Three groups (B, D, and F) are part of organizations that analyze business data on customers, production, or accounting; they disseminate their analysis results to internal and external stakeholders. Three groups (A, C, and K) belong to organizations concerned with analyzing data about the general population; they disseminate results publicly. Lastly, one group (J) does artistic photography and shows it in media and art exhibitions. The aim of this variety of domains is to attempt more general conclusions than if we did an in-depth study of one domain. We return to the pros and cons of this variety in the Discussion.

Workshop preparation: Interviews, Tasks, Data

To prepare for each workshop, we interviewed one person from each group of participants. The purpose of the interview was to understand the domain of work and to identify tasks for the subsequent workshop (see Table 1). We asked open-ended questions about the data the groups use and the analysis tasks they perform. We requested that tasks and data to be used in the workshop were based on actual analyzes that the interviewee had recently been doing. Some persons were interviewed two times to clarify the domain and find useful tasks. We also identified data in raw and various processed forms that would be used during the workshop to remind participants of their work and generate ideas. The interviews also helped identify co-workers that would be part of the workshop.

For each interview, we identified up to five analysis tasks that would form the focus in the workshops (see Table 1, second rightmost column). A total of 23 tasks were collected: for two groups, analysis tasks were not fixed before the workshop; while one group had five tasks described. Tasks could for example be: How does use of the website relate to country of visitor (workshop B), how are galaxy image features related to galaxy properties

	Participant characteristics			Materials used in the workshops	
	#	**Domain**	**Type and magnitude of analysis data**	**Tasks**	**Representations of data**
A	3	Health care policy (Public)	Data on 1m (million) annual admissions to Danish hospitals.	Understand errors in computing costs of hip replacement surgery based on activity information from hospitals.	3 sheets of tabular data and 3 sheets of histograms covering a subgroup of hip replacement surgery.
B	2	Website analysis (Business)	Logs of 2m annual visits to an international corp. website.	Understand how use of the website relates to country of visitor and means of access.	89 printouts of reports from Google Analytics based on website in question.
C	3	Health care policy (Public)	Financial and operations data on 1m annual admissions to Danish hospitals.	Compute costs of births with and without epidural block and understand how changes in configuration of financial accounts influence diagnose group costs.	2 sheets of aggregated costs of patients, grouped by disease category; 14 births split on hospitals and 28 sheets with financial accounts of a specific hospital.
D	2	Phone log analysis (Business)	Logs of 5k (thousand) users' smartphone activity.	Understand how separate subscriber segments use smartphones during a day.	Sketched individual and aggregate data over time for particular segments.
E	2	Astrophysics (Research)	Raw and processed images of 1m galaxies.	Understand relation between image features and properties of galaxies.	Raw and processed images of galaxies in 3 different sizes.
F	3	Logistics (Business)	Positioning information of 10k containers on shipping vessels.	Stow containers into partially loaded vessel at current port minding stability, stresses of vessel and optimal ballast use.	14 sheets of user interface from an actual product used for analyzing loads of containers on shipping vessels.
G	2	Internet game statistics (Research)	Logs of 1m internet game users in-game activity.	How are communicational patterns defined and how do they relate to player age, leveling, and number of players?	20 sheets of: a tabular overview of database tables, a box and whisker plot, 2 scatter plots, and 3 bar charts.
H	2	Information retrieval (Research)	Mapping of 30k rare diseases to 120k medical concepts.	Understand relation between mappings; why these results and why poor/no match.	20 sheets of tabular data describing input and from a semantic mapping tool.
I	3	Information retrieval (Research)	Results of 1k queries to an IR system based on 1m documents.	Gain overview of different IR scores and their relation considering the queries.	3 sheets of tabular data of query results for a rare diseases search engine and aggregates based on 27 IR metrics.
J	2	Artistic photography (Arts)	100k photographs of people in the street.	Sort photographs in categories, construct new categories, select exhibition photographs and design exhibition layout.	100 photograph sheets covering 5 different categories, as well as 5 contact sheets with miniature photos.
K	2	EU air emission statistics (Public)	Statistical reports from multiple public sources.	Find and extract relevant information and analyze sources to understand trends.	8 sheets of paper with data describing air pollution in the EU.

Table 1. Characteristics of participants' domains and data analysis tasks. Numbers of workshop participants are indicated as #.

(workshop E), and how are photographs sorted into meaningful categories (workshop J).

Each interview also resulted in some representation of data to be used during the workshop. We collected 452 sheets of paper containing tabular data, histograms, scatter plots, bar charts, photographs, images, feature images, line charts, geographical maps, and user interface components showing data to use during workshops. Participants brought these sheets of paper to the workshops; in most workshops, additional representations of data were produced during the discussion.

Conducting the workshops

We conducted one workshop for each group of participants; workshops lasted up to two hours (on average 92 minutes). The workshops were held in a meeting room, accommodating up to 20 persons, equipped with a whiteboard of 6 meters by 1.3 meters. We had post-its and whiteboard markers (in 4 different colors), magnets and magic tape available as well as the data printouts that workshop participants brought along.

Each workshop began with introducing participants and facilitators, and explaining the agenda for the workshop. We explained participants the tools that were available.

For each of the tasks identified, we asked the interviewee to walk through the task, the associated data, and the conclusions reached. While doing so they were told to imagine that the whiteboard was a high-resolution display. Next, we encouraged the other participants to discuss how to do the task, how to interpret the data, and to discuss the findings – while reminding the participants that they should use the imaginary display to support their discussion. Figure 1 shows a typical workshop situation: Here, participants discussed how related data could be used in relation to their main data.

When this discussion had lasted about 10 minutes or had dried out, we probed participants with questions in relation to their discussion. The questions come from three sources:

- Information Visualization taxonomies [11,28,40].
- The possibilities enabled by large displays and how participants would use them.
- The tasks brought to the workshop.

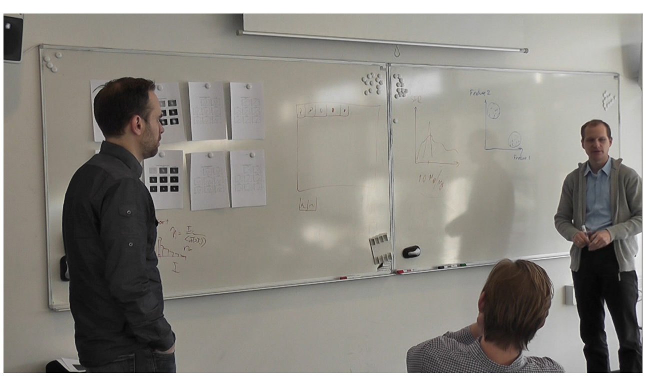

Figure 1. Typical situation in a workshop (workshop F).

When asking questions, we framed or explained them in light of the discussion to ensure participants would understand our questions. For example, we asked "How would you want this shown so as to be able to compare it to the other example?", "Would you prefer to have both a visual representation and a table?", and "How would you use the entire whiteboard to support this task?"

Data Collection and Analysis

Our data comprise notes from the interviews and workshops, data, analysis tasks, and video recordings gathered during the workshops.

We recorded each workshop using two video cameras, each viewing the whiteboard from a different angle. Videos were in 16:9 HD format so as to enable us to observe gestures, pointing, body language, and movement, and were merged into 32:9 video files to be able to easily switch between angles.

Initially, workshops A and B were transcribed and coded by one analyst, both to describe interesting themes to pursue in following workshops and to develop codes. After coding these workshops, we also conducted a collaborative coding session. We looked for themes, topics, and issues related to abundant display space, although other interesting observations were kept as well.

After having conducted all 11 workshops, one analyst coded the remaining workshops. The codes were developed further during this second pass and codes describing activity and general behavior in the workshops were added; we also added codes describing the phase in the workshop (intro, task intro, task discussion, task roundup, workshop summary and pause), interaction on the whiteboard (writing, placing paper, moving paper), gestures (on-screen, in front of screen, in-air), and movement (stepping back, approaching). Following this pass, codes with low coverage were revisited; if we were able to call up instances of these codes from memory, we added them – otherwise, the codes were left out of subsequent analyses.

In the third and final pass, we held short collaborative discussion sessions in which workshop observations were discussed. This resulted in identification of six themes that one analyst related to the coding. For each theme, we identified codes from the second pass that related to these and coded the themes on these; we used axial coding [31] to develop codes further.

RESULTS

The following section first gives an overview of what happened in workshops. Then follows six themes developed during the third analysis pass (see above). The themes concern (1) persistency, (2) showing data side-by-side or one-by-one, (3) space to spread out data, (4) trail of thoughts, (5) movement, and (6) gestures.

Overview of workshop activity

We began each workshop with an introduction (4min). The average time in minutes used for each task broken down in phases was: task setup and introduction (9m), task discussion (30m), and task roundup (3m). Tasks varied much across workshops (see Table 1), but did contain common types of analysis such as comparison between sets of data (10 workshops). Another example was discussing overviewing (all 11 workshops), in some instances in relation to obtaining an overview and in some instances to losing the overview. We ended the workshops in an open dialogue and thanked the analysts for participating (4m).

Participants brought data from their analysis domain to the workshops and used them in various ways on the whiteboard (e.g., attaching them using magnets). In addition, participants drew sketches of user interfaces and different representations of data. Some common types include histograms (used in 6 workshops), tables (9 workshops), and plots (8 workshops); see Figure 2.

Annotations on the whiteboard were coded 20.9 times on average, varying from 0 to 38 instances between workshops, while annotations on sheets of paper were coded 1.3 times per workshop. Placing the paper sheets were coded 6.3 times on average, while moving papers was coded 6.8 times per workshop, varying from 0 to 25 instances between workshops, indicating that in some workshops paper was not used at all.

Participants were actively engaged in discussion during most of the time in the workshops. We saw few pauses in speech lasting more than a couple of seconds. Most participants were gesticulating while speaking. Most gesticulations supported communication between participants and facilitators, yet we coded 172 gestures relating to interaction with the imaginary display.

In all workshops, participants moved along the whiteboard, and closer to or farther from the whiteboard. In 6 workshops (A, C, D, F, G, I), only one participant was active in front of the whiteboard at a time, whereas in the other 5 workshops (B, E, H, J, K) participants shared the whiteboard fluidly. When one participant was active, other participants would sit, but keep engaged in the discussion. We identified 3 typical positions in relation to the display: (a) interacting or looking at the display, (b) interacting with other participants with the back to the display, and (c) away from the display facing it.

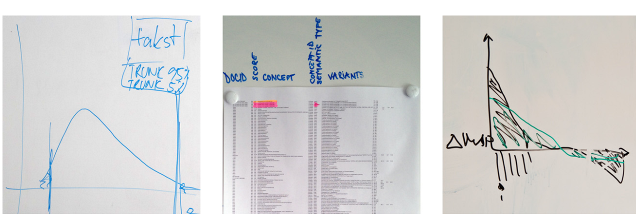

Figure 2. Frequent types of representations used: Histogram (left, workshop A), table (middle, H), and plot (right, I).

Persistency

The most frequent use of abundant space we call persistency: partitioning the display space so that designated areas have a particular purpose in support of analysis throughout a task. Participants' idea behind this usage seems to be that when display space is abundant, one may use more of it to show data for longer periods of time. Persistency was seen in 6 workshops (D, E, F, G, H, J) where participants fixed key variables, data sets, or views to particular areas.

A typical example of persistency was seen in a workshop where participants worked with analyzing how cellphone subscribers use smartphones. In that workshop, an interface was sketched during the workshop (D: 32:30-36:40, see Figure 3 top-left). The top part of the display was reserved for a dimension layer displaying simple data representations (e.g., histograms) of variables preselected among all variables in the system (the examples given were gender, age, smartphone model, questionnaire answers), which could be used to modify data representations in a working area in the central region of the display. Participants also imagined the bottom display area designated for showing a fixed set of groups of data (D: 46:10-46:40).

While most instances of persistency concerned fixed display areas, we saw 2 instances suggesting a need for participants to define persistency relative to their position. In workshop F participants worked with allocating containers onto sections of a ship. They talked about seeing sections of an entire ship in front of them and having related information such as stability metrics and overview of ports placed persistently around this view. Participants went on to imagine the entire ship spread out over the display and having the related information available in their horizontal periphery (F: 36:30-37:00). Having this information fixed in their periphery would enable them to focus on a particular section of the ship while still being able to glance at the important information from time to time. In Figure 3 (top-middle) a participant is gesturing how these views would be positioned.

In the above example, we described variants of persistency pertaining to seeing an overview of the ship and a detailed view of information. We saw instances of persistent overviews in 5 workshops (D, E, F, G, and J) and of persistent detail views in 3 workshops (F, H, and J).

Persistency was talked about or used with raw data, variables, groups of data, and aggregate/calculated information. Recall the example above from workshop D where areas were designated to hold specific variables and groups of data. Likewise, the example above from workshop F involved detailed information. An example of raw data was seen in workshop G (G: 1:21:12-1:21:22), where participants imagined using an area for raw data that could be selected and moved to a more active area for analysis.

Showing data side-by-side or one-by-one

We saw two distinct approaches to how participants worked with multiple representations of data. In one approach, two or more representations of data were used side-by-side. We saw this approach in 10 workshops (all except J). In the other approach, a single representation was changed by interaction, showing data representations one-by-one. We saw this approach in 7 workshops (A, D, E, G, H, I, J).

A typical example of using representations side-by-side was seen in workshop C (39:00-45:20), where participants tasked with understanding cost structures in Danish hospitals analyzed patients with related sub-diagnoses and where they were admitted. Participants used a stacked bar plot showing proportions between individual hospitals. Clicking on a specific bar opened a pie chart next to the other visual representation showing diagnose broken down into procedure codes (see Figure 3, bottom-left). Participants went on to discuss seeing histograms and averages of individual slices of the pie – for example showing distribution over age, admission time, or gender. In this style, representations of data unfold over a series of interaction steps, forming a tree-like path of interactions.

A typical example of using a one-by-one approach was seen in workshop D (46:20-51:35) where participants who worked with smartphone usage logs imagined a middle working area showing a data plot of smartphone usage averaged over a 24-hour period. They wanted to drag variables onto this data plot and thereby let the variables act as filters for the data shown. For example drag the segment *20-29 years* of the variable *age* onto the data plot thereby filtering on this criterion. This is illustrated in Figure 3 (top-left). The boxes in the top of the figure represent variables which can be dragged down onto the graph in the center of the figure to filter the data.

The examples above concern drilling-down in data by filtering on variables. We also saw the approaches of side-by-side and one-by-one used when comparing groups of data. In workshop E (11:25-12:05), for example, participants looked at original grayscale images, processed images, and image feature-plots of two galaxies to compare and understand how visual properties of galaxies were represented in the plots of image features. This configuration of data is shown in Figure 3 (bottom-middle).

The two approaches represent a tradeoff between use of space and interaction. Although space is preferred for many purposes, interaction over time is nevertheless preferred in some situations. For instance, in workshop I (75:15-75:35), participants compared sets of data by flicking back and forth between them. They started by defining what data to compare using checkboxes. Then they talked about viewing data one-by-one: *You could perhaps define two views that are [in] the same space and then say; well can I have one or the other, one or the other* [said while doing a flicking gesture and looking at the data]. They did this to understand

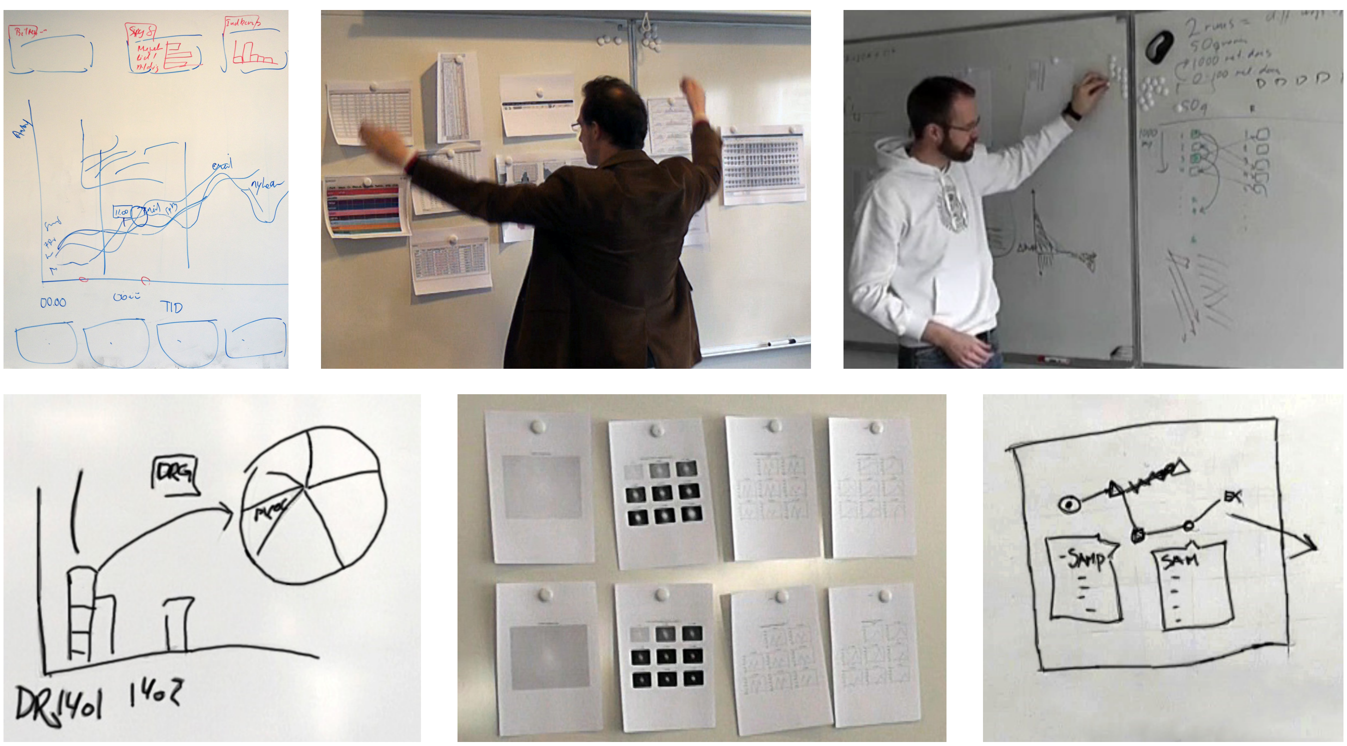

Figure 3. Top-left: Analyzing cellphone subscriber behavior on smartphones. Top-middle: A participant show how information views would be positioned in a user's peripheral view. Top-right: A participant uses a magnet to illustrate a flicking gesture. Bottom-left: Tree of plots. Bottom-middle: gray-scale images, processed images and image feature-plots of two galaxies. Bottom-right: Representation of data processing flow.

the difference between the two views: ... *to see visually, to swap between [the views] and [see] what happens actually* [flicking gesture]. They preferred this rather than having sets of data shown next to each other. This situation is illustrated in Figure 3 (top-right) where a participant uses a magnet to illustrate a flicking gesture.

Space to spread out data

In 3 workshops (D, I, J), participants used space to spread out choices over large areas so that they could select from multiple options shown with rich representations. The abundant display space enabled participants to use several meters of the display for a temporary view to help select from a list of choices or to assign something to an item.

A typical example of this was seen in workshop J (97:18-97:34), where participants were working with categories containing thousands of photos: *Then I am able to take for instance these categories* [pointing gesture towards the area of the categories] *and spread them out over the upper part of the display* [doing a spreading gesture over a large area of the upper display area]. This enabled the participant to assign photographs to the categories.

Another variant of using space to spread out data were seen in workshop I (40:46-41:08), where participants analyzed results from an information retrieval system. Part of this work compared measures of different algorithms. In this situation participants imagined using the overview as an entry point to data: *If we could generate on the fly* [vocal: bouuf, snapping and doing a spreading gesture] *all the measures in one big table* […] *if we rather than having to look at it one by one* [while doing flicking gesture in the air] *could have a starting place with lots of information about, on summary data* […] *and then move to, ok let's go into the details and look at the ranks and what actually happened.*

The use of space to spread out data differs from participants' use of space to view information side-by-side. Using space to spread out data is temporary and typically used when participants need to select or modify data.

Trail of thoughts

With abundant display space, participants commented on the value of being able to see earlier steps of analysis by having these steps represented visually; they also referred back to and used representations of such steps in the workshops. In some workshops, data processing flows were used to represent this idea (A, C, G) and in others snapshots of the display state were shown in small (G, I). We saw examples of such trails of thought in 4 workshops.

An example of using a data processing flow was seen in workshop G (55:10-57:50), where participants drew steps of data processing as vertices and the order of processing as edges. The representation of the data processing flow is shown in Figure 3, bottom-right. Participants explained that it was useful to have an overview of how data were processed and be able to go back and look at earlier steps in the analysis. Results from individual vertices could be represented using histograms or other representations. A related observation was seen in workshop C (39:00-45:20, also described in the section on side-by-side viewing). Here the steps were represented directly by visual representations of results instead of by vertices. When participants wanted to explore a part of the results further, they would press this part, which would make an edge appear that led to a more detailed view of part of the data (see Figure 3, bottom-left).

An example of using snapshots was seen in workshop G (81:57-83:05) where participants discussed how to mark important findings while doing analysis to be able to summarize at the end of an analysis session: *If you could let it make up a summary so you simply could have a description of this [analysis] in time so that you at the end of a meeting quickly could summarize what we have been doing. ... if you simply had the display time your progress along the analysis* [gesturing over the lower part of the screen to indicate a horizontal line of display snapshots] *so that at some point you could say; now we are rewinding to the start of the meeting and then quickly go through the points we have touched upon. ... Then you would be able to do a commented summary [based on this*]. Participants also remarked that marking dead ends in analysis was important.

Movement

The size of the display naturally caused participants to move around in front of the display, and moving closer to or farther from it. Moving away from the display seemed to facilitate obtaining an overview and moving closer seemed to facilitate seeing details. When participants moved in front of the display, they did so to get to data or views of interest, to move out of other participants' view, to gather an overview, or to point to something on the display.

In workshop J (59:40-60:00) for example, participants moved close to the display to look at details in specific photographs and quickly back again to position this detail in their overview: *I can construct an overview of the photographs, I can see what's on the photographs while still being able look at the entire overview.* The sequence of first standing away from the display and thinking, then walking up close to interact with the display and then slowly backing up, as if to make sure things were as expected, was seen in 8 workshops; it was most visible in workshop J. To confirm this observation, we inspected movement patterns in workshop J by sorting still images grabbed with 15 second intervals. Three main categories of positions in relation to the display were observed: interacting or looking at the display (close), with the back turned to the display and interacting with other participants (middle), and away from the display facing it (far). Sorting the grabbed images into these categories showed that participants spent an equal amount of time in all three (close: 34%, middle: 33%, far: 33%).

In some workshops, we observed participants only taking half a step backwards to get distance from the display and to get an overview (e.g., workshop E: 26:40-26:41).

Another variant of movement relates to small movements with both feet on the ground. An example of this was seen in workshop B (23:05-23:07), where participants did a task on one part area of the display that required data placed in another area. To be able to grab the data located far away at the display, one participant leaned backwards, thus getting an improved field of view to the distant display area.

Gestures

We saw 172 gestures with the imaginary display that were significant or interesting enough for coding. We grouped these gestures into three types according to their occurrence in workshops: (a) on-screen (9 workshops, 44 gestures); (b) in front of screen (8 workshops, 43 gestures); and (c) in-air gestures (10 workshops, 85 gestures). Most of these gestures have been described in the literature. For instance, we coded 46 instances of sync- or asynchronous bimanual interactions.

An observation that surprised us was the use of very large gestures (13 gestures in total, 6 workshops). We see the size of these gestures to be related to display space. An example of a large gestures was seen in workshop J (95:50-95:55) where participants talked about changing overall states of the display (see Figure 4): *If there was a permanent image viewing function, which is this one* [pointing to a spot on the display] *having the large view. This is a view which you actually could do like this to* [gesturing with one hand from the left of the display to the right, almost 6 meters] *and draw it all the way over here, because now I just need it to be here*.

DESIGN IDEAS

Our results suggest that information visualization systems could be designed with consideration for persistent views, not only as tool palettes and other interface objects, but also to show and interact with data such as raw data, variables, slices of data and general information views.

Views were fixed to top and bottom areas of the display for specific purposes, thus promoting the center area to a working or thinking area. This area was kept for things that were part of a thought process, whereas items supporting constructing and reconfiguring the working area were positioned in harder to reach positions (i.e., in the vertical periphery). Likewise, areas in the horizontal periphery could be used as persistent areas displaying for instance aggregated information. Participants moved back and forth in front of the display. This implies that such an area may need to move with the user. Participants also moved away from a display, for instance to gain an overview of items on the display. In this situation, these peripheral views may be irrelevant and could be hidden to not block important data.

Participants used views of data both side-by-side and one-by-one depending on the situation. This suggests enabling both styles of interaction with data. It also suggests a need to improve our understanding of when it makes sense to use space rather than interaction.

Figure 4. Example of a very large gesture.

Participants also used one view of data to create new views next to the current view by interacting with parts of data in the view, thereby forming paths of interaction that enabled backtracking. Another method of providing backtracking was to show representations of previous display states, for instance in the bottom display area. This method seemed to be relevant for analysts when constructing a summary of a collaborative analysis session.

Data were temporarily spread out over large areas to enable participants to select from choices. Using space to show choices in rich detail and high resolution seems ideal. When the use is only temporary, these areas may block other data.

Gestures may be relevant to use both on, close to, and from a distance to the display. Large gestures seem to be relevant and perhaps the size of a gesture and the distance to what it refers to may carry meaning in itself.

DISCUSSION

We have presented a cross-domain workshop study of how domain experts would analyze their data with abundant display space. The workshops were analyzed to generate design ideas for interaction and visualization with abundant display space. The most prominent design ideas were:

- Use abundant display space for persistent views of data.
- Use middle center area to support thinking.
- Use vertical periphery to configure middle area.
- Enable both side-by-side and one-by-one views.
- Enable paths of interaction.
- Use abundant display space to support backtracking.
- Use abundant display space to show rich representations of choices.
- Enable use of large gestures.
- Support interaction from a distance.

Relation to Existing Work

In relation to the literature on large high-resolution displays, our design ideas warrant some comments. Earlier work has suggested that large displays promote physical navigation [2]. Certainly, movement in the workshops was necessary as no virtual navigation was possible. However, the workshops suggested that pairs use and switch between parts of the simulated display flexibly. This is similar to findings that high-resolution displays with touch may lead to less territorial behavior (e.g., [20]). The finding that people move not only sideways but also back and forth in relation to the display is related to the recent interest in proxemics for interaction [5].

Although we saw use of abundant display space to support backtracking, probing for styles of interaction related to undo/redo techniques from the desktop such as [27] did not resonate with participants. Implicit use of space to support backtracking seems a sensible way of using abundant display space, and is similar to how [30] represent history. In our workshops, however, history was integrated in the primary view. Participants suggested constructing summaries of analysis by marking important findings and representing these as snapshots of the display, which seems to have a different purpose than both undo/redo techniques and backtracking, and is perhaps similar to what Mahyar and colleagues saw [21].

Our observation of side-by-side and one-by-one views are in line with Gleicher and colleagues' notion of juxtaposition [15]. Here, side-by-side views are similar to juxtaposition in space, whereas one-by-one views reminds of juxtaposition in time and in some instances of blink comparison.

Workshop Methodology

We used cross-domain workshops as a methodology for uncovering new interaction styles and new uses of visualization. In the introduction to this paper, we speculated that cross-domain workshops with simulated large displays might lead to interesting insights. Next, we want to revisit this speculation based on the experience of running the workshops and of analyzing them.

In many and important parts of the workshops we found that participants' imagination was vivid. After a workshop, we showed a participant a large high resolution display. He commented that seeing this display would have made him think differently about the whiteboard during the workshop, which would probably have both positive and negative effects on participants' imagination.

One reason why we were able to derive design ideas from participants seems to be that we used both their behavior and their comments to derive ideas. Another reason seems to be that comparing across domains helps identify common threads of data analysis. The present study has identified some of the same uses of abundant display space across domains as varied as photo management, health care, and container loading.

In other parts of the workshops, it seemed difficult for participants to imagine new technology: it was clear from some participants' dialogue that they thought in terms of the data representations, software, and interaction techniques they know and use today. For instance, in one workshop participants would have alternate terms related to a given sentence by a number describing the part of the sentence to which the term was an alternative. They did not see, however, that with abundant display space the position information could be substituted by placing terms directly around the sentence (similar to a large version of excentric labels [14]). In other workshops, participants would talk about using arrow keys to sift through pictures, or talk about how to access syntax information.

The use of a whiteboard as a large display generally worked well: whiteboards are ubiquitous and can be used right away for drawing and attaching prints. Compared to studies of whiteboard use in visualization [34,38], we saw similar rich and unconstrained use. This suggests that the range of representations and interactions with the whiteboard might be varied enough to inform design. However, we see at least two ways the workshops can be improved.

First, whereas the whiteboard worked well to convey a sense of abundant display space it did not convey any sense of resolution. Most likely, such a sense was developed based on the resolution of the prints that participants carried with them, in addition to the scale at which they drew on the whiteboard. We think that physically large and small prints of data, as well as high and low resolution images may exemplify the role of resolution to participants, making it unnecessary for workshop moderators to explicitly describe or probe for resolution.

Second, we saw a lack of motivation to remove data once it had been placed on the whiteboard. It is unclear how this relates to how people use whiteboards' available space and only erase on an as-needed basis [23]. It might also be related to working out the tasks in the workshop setting (i.e., as a group) which differs from how some of the participants normally work.

Limitations

Our paper has a number of limitations. First, our workshop approach attempts to bridge doing field studies of data analysis to derive implications for design and using models/theories to derive implications. Recommendations derived from this attempt, however, need to be validated using other types of method. In particular, we are interested in trying to implement the interaction techniques developed and test them across domains, following the idea that cross-domain explorations may integrate the concrete (task solution in a single domain) with the general. Second, the number of participants in each workshop was low and thus, we cannot extend our findings to larger group sizes.

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Paper II

Information Visualization and Proxemics: Design Opportunities and Empirical Findings

Mikkel R. Jakobsen, Yonas Sahlemariam Haile, Søren Knudsen, and Kasper Hornbæk

Abstract—People typically interact with information visualizations using a mouse. Their physical movement, orientation, and distance to visualizations are rarely used as input. We explore how to use such spatial relations among people and visualizations (i.e., proxemics) to drive interaction with visualizations, focusing here on the spatial relations between a single user and visualizations on a large display. We implement interaction techniques that zoom and pan, query and relate, and adapt visualizations based on tracking of users' position in relation to a large high-resolution display. Alternative prototypes are tested in three user studies and compared with baseline conditions that use a mouse. Our aim is to gain empirical data on the usefulness of a range of design possibilities and to generate more ideas. Among other things, the results show promise for changing zoom level or visual representation with user's physical distance to a large display. We discuss possible benefits and potential issues to avoid when designing information visualizations that use proxemics.

Index Terms—Proxemics, information visualization, user study, large displays, user tracking, movement, orientation, distance.

Introduction

Information visualization uses interactive graphics to amplify cognition [5]. It can improve many aspects of dealing with large sets data: Visualizations help explore and navigate large information spaces [39], analyze and make discoveries in high-dimensional data [43], and discuss data within on-line communities [51].

Most information visualizations—commercial products and research prototypes alike—are designed for a setting where users interact using a mouse on a desktop-sized display. Recent research has explored how visualizations should be designed for non-desktop settings [27], in particular for large high-resolution displays. Examples visualizations designed for this setting include using tangible input controllers [21], sensing body movements as implicit navigation input [9], and adapting interaction techniques for large displays [19].

We extend this work by using the notion of proxemics to identify design opportunities. Proxemics studies the relation between people as it is expressed in the use of space [15,14]. Compared to early work on proxemics, recent work [13] as well as this paper extend the notion of proxemics to describe also the relation between people and objects (often user interfaces). In research on human-computer interaction (HCI), proxemics has for instance been used to design interaction techniques that change user interface layout based on users' position [3], and to study orientation and distance among devices and doctors in neurosurgery [31]. Previous research has also demonstrated how body orientation and position can be used with visualizations: for implicit interaction with ambient displays [52] and for coarse 3D navigation in microseismic visualizations [32]. We build on previous work to explore how the notion of proxemics can be applied to interaction with information visualization.

The opportunities for proxemics in information visualization are manifold. First, it may be used to adapt visualizations based on the users' position and orientation relative to the display. Second, it could use movements in front of a display to have visualizations follow users' movements or blend as two users get close. Third, we could augment users' backing away from a large display by even further zooming out or abstracting the visualizations. Many other uses of proxemics in information visualizations may be imagined.

This paper explores in particular design opportunities for information visualization based on movement and distance to large high-resolution displays. We focus on using movement and distance because earlier work has emphasized physical navigation as important when using large displays [2] and in group work [20]. We explore spatial relations only between a single user and visualizations; exploring relations between people would provide more opportunities, but is beyond the scope of this paper. The opportunities are illustrated with a design space and with sketches; the opportunities focus both on supplementing other input techniques and on replacing them. We also show how earlier work that has not explicitly used the notion of proxemics (e.g., [52]) can be understood through proxemics and potentially benefit from its analytic framework. We select a subset of design opportunities to implement and test in three user studies: (1) navigation by physical movement, (2) querying coordinated views by movement, and (3) adapting visual representation to distance. We do so to generate design ideas, but also to provide initial data on the usefulness of combining information visualization and proxemics. Our approach is to ground some opportunities in empirical data rather than to give an exhaustive systematic review of the opportunities or to present in-depth data on a single case.

We contribute (a) an initial analysis of using proxemics for information visualization, (b) prototypes of information visualizations that adapt based on tracking of their users, and (c) an evaluation of a set of proxemics visualizations. The argument is that proxemics may offer promising design opportunities for non-desktop visualizations; we think such opportunities are valuable to both researchers in visualization and to designers for large displays.

1 Related Work

The term proxemics is due to Edward T. Hall [14,15], who used it to describe the study of "how man unconsciously structures microspace—the distance between men in the conduct of daily transactions, the organization of space in his houses and buildings, and ultimately the layout of his towns". Among other contributions, he related physical and social distance in a set of four zones, from intimate space (less than 46cm between people) over personal and social space to public space (over 3.7m). Hall discussed how social, gender, and cultural factors may mediate this relation. Much research has built on and extended Hall's work, applying it for instance to design [47], human-robot interaction [33], and HCI.

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Manuscript received 31 March 2013; accepted 1 August 2013; posted online 13 October 2013; mailed on 5 October 2013.
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Proxemics is increasingly used in HCI, both as (1) a notion to understand and analyze collaboration and interaction, and (2) as a notion to drive the interaction among users and devices. The first point has been studied in computer supported collaborative work (CSCW), where the relation between physical distance and perception of social distance has been a key issue [37]. Applications in CSCW include a study by Hawkey et al. [17] investigating the relation between proxemics and collaboration success with a large wall display. Stretching proxemics to include the relation among users and devices has led to several descriptive accounts. Mentis et al. [31] studied orientation and distance among devices and doctors in neurosurgery using notions of proxemics. Jakobsen and Hornbæk [20] used proxemics to describe interaction in front of a large display.

The second point above has in particular been inspired by Marquardt and Greenberg's notion of proxemic interactions [13]. Their work extends the notion of proxemics so that it pertains not only to relations among persons, but to relations among people, digital devices, physical objects, and the environment. They consider five categories of proxemic dimensions particularly for ubiquitous interaction (which is relevant more broadly for HCI):

- *Distance*, the physical distance between entities, either given as a continuous measure or relative to discrete zones. In Lean and Zoom, for instance, semantic zooming is based on the users' distance to a laptop screen [16].
- *Orientation* concerns which direction a person (or other entity) is facing. This has been used, for instance, to adapt presentation software to different views depending on which way the presenter is facing [13].
- *Movement* concerns the changes in distance and/or orientation over time. For instance, personal territories on tabletops can be adapted when one user approaches another user's space [26].
- *Identity* concerns distinguishing between entities. For instance, a display may respond differently to the movement of a mobile phone than to the movement of a person [13].
- *Location* describes the place of interaction. A simple instance is the presence of a person in a room.

A recent toolkit helps detect and react to these dimensions [29].

Some earlier work has used related types of movement to control interaction, without explicitly using the notion of proxemics. Vogel and Balakrishnan [52] presented a display system that supported a smooth transition from public use of the display, through implicit interaction at a distance, through up close, personal interaction. Ju et al. [23] presented an interactive whiteboard that sensed users' distance to the board for switching between modes in using a whiteboard, in particular authoring and ambient use. Marquardt describes gradual engagement in providing connectivity, information exchange and transfer as a function of proximity [28]. Marquardt and colleagues give many other examples [13,30]. Work on navigating virtual environments has also used movement and orientation extensively. For instance, Souman et al. [48] described how an omnidirectional treadmill allowed participants to walk in any direction they wanted in a virtual environment, with information in a head-mounted display being updated based on their walking. Such work differs from the focus of the present paper in that movement and orientation are used to generate a view (say, in a head-mounted display) of a virtual environment corresponding to a particular position of the users' head; instead, we consider uses of proxemics data for changing visualizations of abstract data.

The present paper uses the notion of proxemics to drive innovation in interaction with information visualizations. One reason to do so is that the notion of proxemics might help generate interesting designs, beyond those described in the literature. Another reason is that to our knowledge, no paper has attempted to relate proxemics and visualization, despite the interest in using visualization on large displays and despite the frequent observation that movement [2] and orientation [4] play key roles in interaction with large displays. A third reason is that even though earlier papers have used movement to control interaction (e.g., Vogel and Balakrishnan [52]) they rarely relate to the information visualization literature and do not evaluate visualization tasks. Thus we proceed to discuss the relation between proxemics and visualization.

2 Design Opportunities

As argued earlier, a variety of design opportunities may be generated from the proxemics literature. Because these have not been explored in relation to visualization activity, we next discuss some design opportunities, in part summarized as the design space in Table 1. Some of the opportunities are implemented as prototypes and evaluated in user studies in the second half of the paper (marked #1, #2, or #3). Some entries in the table are blank, either because they are uninteresting or because we have yet to come up with, or find in the literature, a compelling example.

The design space is organized from established views of key characteristics of proxemics and information visualization. To this end we choose categories from earlier work on proxemics [13] and information visualization tasks [18].

Many alternatives to these two choices exist. With respect to proxemics, earlier definitions emphasize different types of

Table 1. Combinations of information visualization tasks (excerpt from [16]) and proxemics categories (excerpt from [24]). The symbols #1, #2, and #3 refers to design opportunities that are tested in the second part of the paper.

		Information visualization task						
		Visualize	Filter	Sort	Select	Navigate	Coordinate	Organize
Proxemics category	Distance	Show details when close/ aggregates when far (#2)	Filter items depending on the physical distance to user (body fisheye)	-	Distance increases selection scope (#2)	Focus and demagnified context at distance	Brush-and-link close data	Distance-dependent workspaces
	Orientatio n	Visualize for different viewing angles	-	Sort by variable selected by orientation	Coarse selection by orientation	Head orientation controls zoom center (#1)	Indicate related areas through orientation	-
	Movement	Switch between encodings by moving (#2)	Dynamic querying when moving (#3)	Sort by variable selected by movement (#3)	Coarse selection by movement	Zoom and pan by moving relative to display plane (#1)	Selected views move along with user (#3)	Reorganize windows in workspace
	Location	Contextual visualizations	Switch between subsets	-	-	Overview and detail in left to right	-	Location-dependent perspectives

proxemics. We chose the much cited taxonomy of proxemic interaction [13], because it captures the relations between people and devices like large displays, which is our focus. With respect to information visualization, a host of alternative models exist. We decided against relatively low-level models (e.g., [1] of information visualization because we think the initial promise of proxemics is to enhance higher-level tasks. We also decided against taxonomies focused on data (e.g., [24,45]), because they were not easy to combine with the proxemics taxonomy. Finally the visualization taxonomy used integrates many aspects of earlier work, for example including most tasks in Shneiderman's task by data type taxonomy [45].

The resulting design space does not include all categories: Some categories of proxemics are less applicable to single-person interaction with visualizations on a large display (e.g., Identity). Similarly, some visualization tasks do not map well to proxemics (e.g., Derive). The opportunities presented here are intended to generate design ideas. Other possibilities exist that could be more useful than the examples given here.

2.1 Distance

Viewing distance is important in using information visualization on large high-resolution displays: Users can step back to get an overview and to navigate [2] or to see patterns in data [8]. However, earlier work has mainly studied visualizations that do not change with user's distance. Vogel et al. [52] is a notable exception as they adapt visual representations and interaction modes to discrete distances. Below we describe how visualizations can adapt and react to distance for particular visualization tasks.

Visualize. Visual encodings may dynamically change with the user's distance. Different tasks can thus be supported at varying distances, for instance by showing aggregate representations at a distance and details up-close. This is illustrated in Fig. 7, where each level of aggregation is associated with a discrete distance zone. The alternative, combining the data in the same static visualization, can overload the display and potentially overwhelm the user. While we focus on the spatial distance between user and display, the distance of a hand-held display relative to a large display could similarly be used for semantic zooming in for instance graph visualizations [49].

Filter. Distance can be mapped to a variable so as to allow filtering out data. For instance, adapting the generalized fisheye view [11] to a large display, could help users focus on the most relevant items; items are filtered out if they have a degree-of-interest below a threshold that grows proportional to the user's distance to the display. More interesting items can be made prominent or shown in detail at a distance while other items are aggregated.

Select. Distance can influence the scope or granularity of user's selections. For instance, Peck et al. [38] describe a multi-scale interaction technique that "chang[es] the user's scale of interaction depending on their distance from the current object(s) of interaction."

Navigate. One possible visualization that adapts to large displays for supporting multi-scale navigation is focus+context: As the user steps back from the display, selected elements in focus can be magnified to remain a constant size in the user's field-of-view; in effect those elements are brought closer together, for instance to support comparison, while the context is demagnified (rather than being filtered out as done in the generalized fisheye view discussed above). This is illustrated in Fig. 1. Another idea is to relate distance to zoom-level, so that when a user moves away from the display, the zoom level changes.

Coordinate. Whereas most coordination of views relies on explicit actions [36], distance to particular views in the display may provide for implicit coordination. For instance, depending on which graphs that are close to the user, they could automatically become linked, so that data points selected in the one are highlighted in the others.

Organize. Views can be reorganized for interaction when the user stands within touching distance of the display (e.g., showing data views and widgets for dynamic querying), while larger overview-providing views are shown when the user is standing at a distance.

2.2 Orientation

Although orientation is used extensively in virtual reality, it is rarely seen in research on information visualization. Research that comes close are the ChairMouse [9], which used the users' rotation on a chair to control cursor movement, and the study by Bezerianos and Isenberg [4], who looked at the role of angle and movement in perception on large displays. Neither study used orientation to adapt visualizations.

Visualize. Visual encodings that become distorted at extreme viewing angles cause problems [7]. A visualization can dynamically change to a visual encoding that is more robust to extreme viewing angles, based on its orientation toward the user. Related techniques are E-conic, which dynamically corrects the perspective of windows [29], and Screenfinity, which rotates, translates, and zooms content to ease reading while users pass by large displays [42].

Sort. Ordering data helps reveal trends or clusters of values. The most common method of ordering, sorting records by one or more variables [18], could be supported by detecting the user's orientation toward a particular variable (e.g., a column in TableLens).

Select. Orientation may supplement other pointing input for selecting data points in visualizations. For instance, a user's motor space with a pointing device can map to a particular view, which is selected by changing orientation (see Fig. 2).

Navigate. Orientation may control navigation by giving additional information about the user's current focus. For instance, orientation may be used to enrich the parts of the display that the user focus on or (as will be experimented with in study #1) to control the point around which zooming is performed.

Coordinate. Orientation can support exploration across views. For instance, body and head orientation can be used together for indicating distinct areas of interest, so that relations between data in those areas can be visualized.

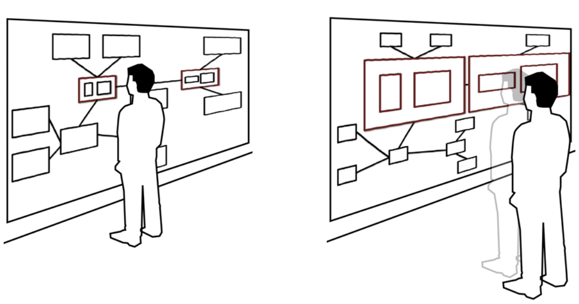


Fig. 1: Distance-based focus+context: Focus elements are selected (outlined in red) while up close (left). As the user steps back, the focus elements are magnified (right).

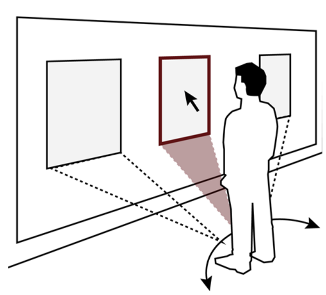


Fig. 2: Selecting view by changing orientation relative to the display.

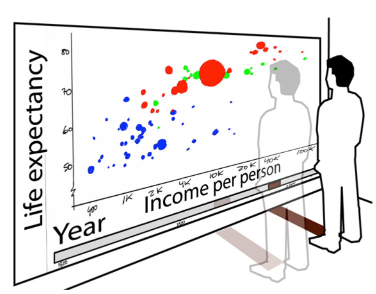


Fig. 3: Changing a dynamic query slider by moving.

2.3 Movement

Visualize. Study #2 will present an example where movement is used to change the encoding of visual representations.

Filter. The spatial relation between the user and a dynamic query slider can be used for filtering. By mapping the user's position to the slider in the display, the user can move relative to the slider in order to change the value. For instance, in Fig. 3 the user's lateral position maps to a timeline: in that way, the user can move right towards the most recent data.

Sort. In study #3 we explore the use of movement to select a variable for sorting a table of data items.

Select. Movement could be used for coarse selection of a view in order to help users select data points in a visualization.

Navigate. Users' physical navigation in a large display can be further supported through view manipulations. For instance, physical navigation can be extended through movement-based zooming and panning: moving forward to zoom in and back to zoom out; moving sideways to pan. This is related to work in virtual reality that have used omnidirectional treadmills to allow movement (e.g., [41]); such studies have typically strived to make rendering of the virtual reality smooth and realistic, not to use movement to adapt interactive visualizations.

Coordinate. Selected views could move with the user's position, for instance to allow comparison across views that are otherwise too far apart to be viewed simultaneously.

Organize. Manually reorganizing visualization views, legends, and controls can be tedious, particularly on a wall-display. However, related views and legends could be automatically reorganized depending on the user's movement relative to the workspace in order to fit the user's focus in a task.

2.4 Location

Visualize. Facilities for creating new visualizations could leverage contextual information from the location so that they are tailored to that particular context.

Filter. Visualization views could be filtered to show different subsets of the data as the user's switches location.

Navigate. To aid navigation, different visualizations that are aimed at taking a broad view of the data (overview) and at specific, detailed investigations of parts of the data (details) may be anchored to different physical locations. For instance, having an overview perspective on the left part of a large display would allow the user with custom visualizations tailored for coordinating several detailed investigations on the right part.

Organize. Different configurations of views may be shown at different locations in order to give different perspectives of the data (e.g., when the user stands near the left side of the display, the rest of the display changes to show information related to the views at that location) or to provide stations for different activities (e.g., monitoring while seated in a certain part of the room).

2.5 Prototyping and testing opportunities and options

The techniques that we prototype and test in the next section present a sample of the design space (see Table 1) selected to probe interesting options. First, we wanted to study one of the simplest cases of linking proxemics and visualization: linking movement of the body to zooming and panning. It is unclear if continuous or discrete measures are most appropriate in that case, and also whether to base interaction on absolute or relative movement. Second, we wanted to compare continuous measures of proximity (e.g., controlling filters through movement) to discrete measures (e.g., levels of aggregation for discrete distances). Third, proxemics may be used to control fluid visual transitions (e.g., zooming, panning) and discontinuous changes (e.g., change encoding, linking movement to selection of variables). We wanted to see if either is more useful or more sensible linked to proxemics data. Fourth, a potential use of proxemics data is to make things appear to be constant size (adapting for instance a graph based on distance) or in the same relative location (e.g., always near the users right arm). We wanted to explore such effects. In sections 4.1, 5.1, and 6.1, we explain the designs we have studied in detail.

3 Overview of User Studies

Whereas the exploration of design opportunities has identified novel and interesting designs, it has not provided any data about the usefulness of such designs. Next, we therefore present three user studies aimed at obtaining such data. The studies aim to provide initial, qualitative data about usefulness by having participants use and compare designs. The studies are lightweight (i.e., each participant interacts for about 40 min) and formative (i.e., qualifying and developing design opportunities rather than finding a "best" option).

This choice of method requires justification. The overall aim of the present paper is to explore design opportunities. We therefore decided against running a controlled experiment, as done in many evaluations of information visualizations and of proxemics [19,22,55]. Instead we wanted to gain empirical insight on a range of design possibilities. We also wanted to avoid rushing to experimentation (as warned about by Shadish et al. [44] and Greenberg and Buxton [12]). We decided against some of the other methodologies for evaluating information visualizations [6] because they mostly assume a hi-fidelity and well-defined design or require a specific application domain, task set, or user base. The former is not the case for the combination of information visualization and proxemics, and the latter seemed to constrain finding and developing design opportunities.

3.1 Commonalities of the studies

The three user studies presented next have a common structure (see Table 2). First, they all have six participants. This number is often recommended for formative user studies [35] and while it gives low power (in the sense of being able to detect quantitative differences, see [7]), it does allow us to gain qualitative insights about usefulness.

Second, all studies use one or two combinations of proxemics/visualization and a reference interaction style. It has been shown that users generate more comments when exposed to several

Table 2. Overview of user studies. Categories refer to the information visualization tasks and proxemics categories in Table 1.

Study	Categories	Users	Interfaces	Tasks	Data
#1	[Navigation] + [Move, Location]	6	(a) Absolute: Navigation by absolute movement (b) Relative: Navigation by location (c) Baseline: Virtual navigation with gyro mouse	Three tasks involving maps, adapted from [8], [41]	Map from OpenStreetMap
#2	[Visualize] + [Dist, Move]	6	(a) Distance-controlled detail/aggregation (b) Baseline: Interaction with gyro mouse	Five tasks adapted from [43]	Data sets of 1000-3000 homes (5 attributes)
#3	[Filter, Sort] + [Dist, Move]	6	(a) Position-controlled variable selection and brushing (b) Baseline: Interaction with gyro mouse	Five multi-variate analysis tasks [39]	406 cars (8 attributes) [44]

alternatives than to just one [50].

Third, we collect qualitative data from the studies. In addition to capturing preference data, we have at least two persons observing users while interacting: the observers take time stamped notes that can be referenced and coupled to video recordings during analysis.

Fourth, while the studies are formative, we prescribe tasks for users to solve. The idea is to ensure that they engage in demanding tasks so as to experience and be able to discuss the usefulness of the interaction styles. All tasks were adapted from previous studies of information visualizations.

3.2 Participants

In all, 18 participants (4 female), ages between 23 and 37 years (M = 29.8), were recruited by word of mouth; six participants for each study.

3.3 Procedure

The procedure was similar across studies. Participants were welcomed to the study, and informed of its purpose. They were introduced to the wall-display and the interfaces, and the tasks were explained to them. Participants then completed a set of tasks with each interface. For each interface, the experimenter first explained its use and participants were given time to try using it. Participants were then given the tasks, one at a time. They were encouraged to ask questions during the experiment. After completing the last task with an interface, we asked participants about their experience with the interface they had just used, including its benefits and drawbacks. Finally, after having completed all the tasks, participants were interviewed about each of the forms of proxemic interaction provided by the interfaces.

3.4 Data analysis

Sessions were video recorded and the experimenter and one or two additional data loggers took notes. Each study was analyzed immediately following its last session using the Instant Data Analysis technique [25]. For the analysis, the experimenter and the data loggers gathered in front of a whiteboard. Observations from the notes and comments from interviews were discussed. When an important issue was identified, it was written on a post-it note and put on the whiteboard. The notes were categorized into themes. Based on the clusters of post-its on the whiteboard, the most important findings were written down with clear references to the observations and any supporting video recordings. On average, the analysis session lasted around two hours.

3.5 Technical setup

Participants used a 24 megapixel display that measures 3m×1.3m. The display consists of 4×3 tiles projected from the back by 1920×1080 projectors. Projectors are manually aligned so as to minimize seams between tiles. The display was run by a single computer running Microsoft Windows 7. The room in which the display was set is 3.5m wide and the distance from the display to the back wall is 2.95m.

For input we used a NaturalPoint OptiTrack motion capture system (www.naturalpoint.com/optitrack/) that tracks, via reflective infrared markers attached to a baseball cap, the location and orientation of the participant's head. Participants also used a wireless gyroscopic mouse. The mouse cursor was enlarged to its maximum size.

4 Study #1: Navigation by physical movement

The first study investigates the potential of using physical movement in the zoom+pan visualization technique.

4.1 Conditions

Three variations of a zoom+pan interface were used for navigating geographical maps. In all conditions, a Gyro mouse was used for interacting with targets in the tasks.

4.1.1 Absolute: Navigation by absolute movement

This interface uses a direct mapping between participants' movement and movement of the map. The user moves toward the display in order to zoom in (i.e., to see details) and away from the display to zoom out. This is illustrated in Fig. 5 (a-c). Movement is combined with head orientation for zooming. A crosshair indicates the point where the ray cast from the cap worn by the user intersects the display, and zooming is centered on that point. Lateral movement controls horizontal panning: Moving left causes the map to move right; moving right causes the map to move left. Our initial intent was to map floor position directly to map position. However, to keep panning speed at a reasonable pace when the user is close to the display (i.e., at high zoom factors), we reduced the floor-to-map movement ratio. This restricts the panning range when close to the display. Head orientation is used for panning up and down. Pitching the cap so that the ray intersects the display plane above or below the display causes the map to pan vertically at a fixed rate.

4.1.2 Relative: Navigation by location

In this interface, participants control zooming and panning by moving relative to a 75x75 cm rectangular region in the center of the floor, illustrated by Fig. 5 (d-f). The map moves right when the user's body is left of the region; moves left when the user's body is right of the region. Similarly, the map zooms in when the user has stepped toward the display from the center region; zooms out when the user has stepped backwards from the center. The zoom rate is inversely proportional to the zoom level so that when zoomed in to a detailed level, the zoom rate is lower. The use of head orientation for zooming and for vertical panning is similar to Absolute.

4.1.3 Baseline: Virtual navigation using mouse

In this condition, the user operates the interface using only the gyro mouse. The interface resembles widespread mouse-operated map interfaces (e.g., Google Maps): The map is panned by clicking and dragging with the mouse; the map is zoomed by rolling the mouse scroll wheel. Mid-air input techniques for zoom+pan interfaces [34] allow more efficient navigation than the baseline interface we used here. However, we did not aim for performance, but rather a simple-to-use mouse-based interaction style that we expected users to be

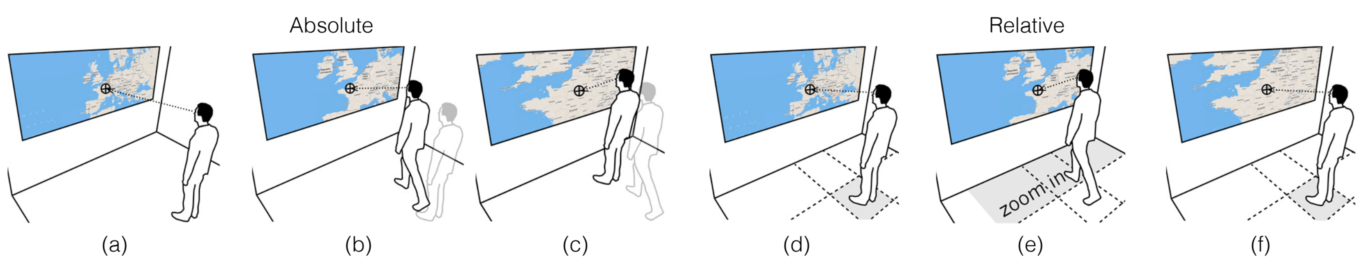


Fig. 4: Zooming in the two conditions that use proxemics in Study #1. In Absolute (a-c), the zoom level increases as long as the user keeps moving toward the display, and stops zooming when the user stands still. In Relative (d-f), the zoom level increases, at a constant rate, as long as the user is within the zoom zone (e). Zooming is centered on a crosshair, which indicates the point where the ray cast from the user's head intersects the display.

familiar with.

4.2 Tasks

Participants performed a series of tasks using a map obtained from OpenStreetMap (www.openstreetmap.org) at different scale levels. The following types of task adapted from [19,46] were used:

- *Navigate*: Participants had to navigate to a clearly marked target and click on it with the mouse. Then a new target was shown, until participants had navigated to ten targets.
- *Trace*: Participants had to trace a railway, where targets were placed close to ten selected stations. Participants had to move each of the pins onto the station using the mouse.
- *Search*: Participants were handed a description on paper of a location (e.g., "Near 'city' find 'lake'") and they had to point out the location. Participants were given three locations to search for.

4.3 Results

We present only results that relate to the use of movement and location to control navigation. In the instant data analysis, four themes emerged.

4.3.1 Using your body for navigation was liked

Several participants said they liked controlling navigation with their body: it is a "nice concept to use your body to move" and "it is nice that you move a lot, particularly in a work environment". Reasons for this view varied. Two participants mentioned that movement was intuitive, three that movement required less effort than the mouse, and two perceived movement to be faster than using the mouse.

4.3.2 Observed benefits and drawbacks of using body

We saw much movement in the Absolute and Relative conditions. Body movement was expected as it controlled navigation. Some observations were nevertheless surprising. One participant transformed the navigation task of finding and clicking an object at high magnification to a smooth movement from the back of the room (zoomed out) to the display (zoomed in). Several participants moved to the back of the room in preparation for receiving the next task.

We noticed a lot of awkward movement. Some participants moved very slowly, some expressed uncertainty about the size of steps to take. Also, movement of your body is difficult to use for fine-grained navigation and it is hard to stop panning as quickly as with a mouse. Some participants adopted particular movement types to deal with these limitations. Three participants leaned rather than moved to control location; two participants kept a foot in the center of the Relative condition while lunging forward or to the sides (one participant mentioned the similarity to dance-mat games).

4.3.3 Movement versus location

A key difference among conditions was the use of movement for navigation versus using location for navigation. Participants were split in their preference for either technique (movement: 3; location: 2; one undecided).

Navigation by movement was well received. Two participants commented that this technique was intuitive, in particular because there was a direct relation between your movement and what happened on the screen. Another difference was the freedom to move around. With Absolute, one participant found "a lot of freedom to move all over the place"; two participants contrasted this with feeling "restricted" and unable to "move freely" with Relative.

Navigation by location was liked for several reasons. One reason was that "zooming was nice here" because one could zoom without getting too close to the screen; when using movement to zoom, participants by definition were close to the screen when they had zoomed a lot. One participant mentioned the benefit of a stable center, in contrast to navigation by movement where the display was changing much of the time. However, participants had to keep track of their position relative to the center. They described how you were "fixed to the center" and that it "requires concentration to keep track of zones".

4.3.4 Design ideas and variations

Several design ideas came up. Rate control was mentioned as an improvement for Relative, so that the speed at which panning and zooming was done depended on your distance to the center point. This would increase the issue of small movements causing large steps in navigation, which is why we did not implement it in the first place.

Movement did not control all aspects of navigation in Absolute or Relative. Head pitch was used to control panning up/down, which caused unintended panning when participants looked down. Participants suggested the use of alternative means for controlling panning, for instance by using gestures.

5 Study #2: Adapting Representations to Distance

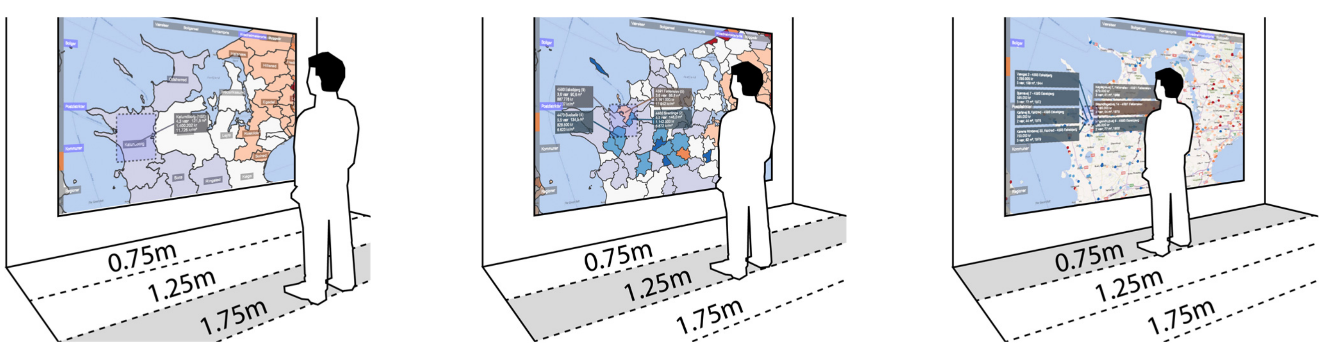
The second study investigates adapting visualizations based on the user's distance and location.

5.1 Conditions

Two variations of a map-based visualization of real-estate data were used. The visualization allows the user to vary the visual representation of the data (individual homes or geographic areas) and to select areas for calling up details on demand. A diverging color scale is used to indicate how the value of an attribute, which the user can select from a menu (e.g., price per m^2), is above or below the mean value of that attribute.

5.1.1 Distance-based aggregation and details on demand

This condition uses distance and movement. First, *distance-based aggregation* changes the visual representation based on the user's distance to the display (see Fig. 7). At less than .75m, individual homes are shown as points. As the distance increases, the



(a) Aggregate, municipalities (b) Aggregate, postal districts (c) Individual homes

Fig. 6: Techniques used in Study #2: Distance-dependent aggregation of real-estate data by geographic area in (a) and (b); details on demand for geographic areas in (a) and (b), and for individual homes in (c); multi-scale selection of map area.

representation changes to show data aggregated on geographic areas (.75m: postal districts; 1.25m: municipalities; 1.75m: regions), and using larger font sizes. Transitions between representations use alpha blending over a 20cm distance. Second, *movement-based Excentric Labeling* [10] gives details about homes within a selection box that follows the user's position horizontally and moves vertically with the pitch of the user's head. Third, for *multi-scale interaction* [38], the selection box grows in size with increasing distance and details are shown for data at higher scales: homes, districts, or municipalities. Fourth, *movement-based change of color encoding*. When the user is more than 2.5m away from the display, the attribute menu (shown in the top-center area of the display) responds to the user's lateral movement: Moving left or right causes an indicator to move to another attribute that will be color-encoded.

5.1.2 Baseline: Gyro mouse

In this condition, the user operates the interface using only the gyro mouse, that is, for changing the visual representation of home data and for selecting the area of the map for which details are shown. The mouse scroll wheel maps to distance in the other condition: scrolling the wheel changes the representation, the size of the selection box, and the level of details that are shown. The four representations of home data are placed on a vertical slider in the left side of the visualization, with an indication of the representation that is currently shown. The selection box is moved with the mouse cursor (that is, while the mouse trigger button is pressed); and details remains fixed when the user stops moving the mouse cursor.

5.2 Tasks

Participants performed the following tasks, some adapted from [53], with subsets of a real-estate database:

- Find the region that has the lowest average price per m^2 (or lowest average number of rooms).
- Find the municipality in a given region that has the highest average asking price (or largest average area).
- Find the home in a particular postal district that has the largest area (or smallest area).
- Find the postal district in a particular municipality that has the highest average price per m^2.
- Find the most expensive house in two (geographically remote) municipalities.

5.3 Results

Three themes related to distance and movement emerged in the analysis.

5.3.1 Use of distance makes sense and "works well"

Four participants described the Distance condition as natural, intuitive, and making good sense. For instance, one said it was "natural to use the body", another that it was "intuitive to get more information in less space when up close. It works very well."

In relation to aggregation of data with increasing distance, one participant said that it was nice that there was not much data when standing back.

Several participants seemed to change between representations with ease by moving. In particular, we observed three participants that moved back and forth repeatedly to switch between representations for solving tasks that involved relating homes or districts to municipalities. Changing representations using the mouse seemed less fluid, and participants glanced more often at the slider at the left.

5.3.2 Discrete distance zones versus free movement

However, using distance did not work equally well for all participants. For instance, one participant said that although it was natural to move, he had to think more while moving than using the mouse. Another said that she had to remember to stand still at a distance.

One drawback, which was clear from our observations and from participants' comments, relates to the discrete distance zones: To see certain information, the user is bound to a certain distance. From our observations this was a problem for one participant in particular, who said that it is "natural to step back for overview, but then the data I want to overview disappears." In the mouse condition, this participant solved the tasks while standing noticeably farther from the display than the other participants: He read details about individual homes from around 1.5m distance. Other participants made related comments. One said you have to get close to see details on individual homes, but then "up close, I had trouble keeping an overview of it all."

5.3.3 Details-on-demand too sensitive to movement

All the participants said they liked the mouse better for selecting the area to show details. One reason is that the mix of using body position and head orientation for selection was confusing.

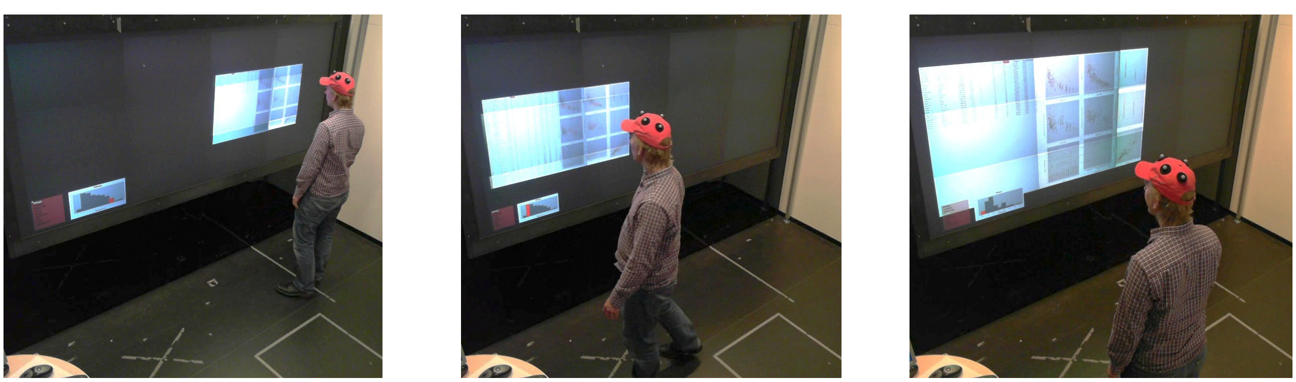
Participants suggested different ways of improving details-on-demand based on movement. Three participants said that they wanted to use their hands to "lock" the view of details or for selecting houses, when they were within reaching distance. Also, two participants suggested leaning close to lock the view of details. *Details on proximity*, or using head position relative to body position, could be a promising design variation.

6 Study #3: Dynamic Query by Movement

The last study investigates the use of movement for attribute selection, brushing and linking, and filtering of multivariate data.

6.1 Conditions

Participants used two variations of an interface containing multiple coordinated views of data about cars. The interface comprises a window containing nine scatterplots and a data table, a view showing a histogram for an attribute, and a view listing the available



(a) (b) (c)

Fig. 8: Techniques used in Study #3: User brushes the bars in a histogram by walking sideways, (a) to (b); the views move to stay in front of the user. The user then moves backwards in order to select another attribute (c); the views scale to remain at a readable size.

attributes. If the user selects an attribute from the list, the histogram for that attribute is shown and the data table is sorted by that attribute. For visualizing the histogram, the values of most attributes were binned to produce 10 bars. For attributes with less than 30 values, each value had its own bar (e.g., model year of cars span 12 years). Histogram bars can be selected: the corresponding data points are shown by filtering the table and marked red in the scatterplots.

6.1.1 Position-controlled variable selection and brushing

This condition uses distance and movement. First, the attributes in the list are mapped to discrete distance zones, 1m (the first attribute) to 2.5m (the last attribute) from the display. The user selects an attribute by moving closer or farther from the display, shown in Fig. 9 (b-c). In the attribute list, a circle indicates the user's position relative to the attribute zones. Hysteresis tolerance is used for transitions between the zones of two variables: The user enters and exits a zone at separate distances. This helps avoid unintentional switching back and forth between two attributes. Users' sideways movement is used for brushing over bars in the histogram: The user's position along an axis parallel to the display maps to the x-axis of the histogram, see in Fig. 9 (a-b). One bar is selected at a time. The physical space for brushing (from leftmost to rightmost bar) spans 1.65m in the center of the display. To enable users to read the data while they move, the views are scaled depending on the user's distance. Also, the window containing the table and the scatterplots is positioned according to users' position. The other views remained fixed.

6.1.2 Baseline: Gyro mouse

In this condition, the interface is operated using only the gyro mouse. Attributes can be selected from the list by pointing and clicking with the mouse cursor. Histogram bars can be brushed by clicking on the bars. Views are fixed in a size corresponding to standing 1.5m from the center of the display in the Position-controlled condition.

6.2 Tasks

Participants performed five types of task adapted from [54], using a dataset with eight attributes for 406 cars [40]:

- Find the car that has the most power among Ford cars.
- Is there a correlation between engine power and weight?
- Does Dodge make more car models than other American manufacturers?
- Please categorize car models into two types: one consisting of cars with poor mileage and one consisting of cars with good mileage. Try to take model year into account. Which has most models?
- State the conditions for your ideal car and identify it using the interface.

6.3 Results

Three themes related to distance and movement emerged from our analysis.

6.3.1 Physical mapping of data

Participants liked the idea of mapping physical space to data space. After having used both conditions, one participant said: "Distance for selection of variables seems very natural"; another described it as fun, but said he felt more efficient when using the mouse.

Participants were split on preference for using movement and using the mouse; all suggested combining the two forms of interaction, one reason being that they could change variables using the mouse. They also suggested adding a lock to position tracking so as to be able to approach the display or step back from it. One said "[I would like to] be able to lock such that I can walk closer to something and then unlock it again"; another that "[I would like to] be able to lock variable choice such that you don't change in error, when you are busy." One participant demonstrated this by taking off the tracking cap so that he could move without changing a variable.

One reason why participants wanted such a lock was because they found it difficult to keep the attribute selected while moving sideways to brush bars. Participants were observed to "drift" in distance to the display while brushing; this could result in abrupt changes of selection. It seems this issue caused some participants to move more cautiously and to look at the histogram.

6.3.2 Scaling

Four participants disliked the way the views were scaled and positioned depending on location. They suggested instead a fixed size (and using a locking mechanism as suggested above to be able to look closer at an item). Three participants suggested that the location-dependent scaling and positioning could be improved by moving and scaling in discrete steps, instead of continuously.

One participant got confused when pointing at the scatterplots, because it scaled when he walked closer to the display while doing so. This participant proposed zooming in when approaching the display (similar to the absolute condition in Study #1). In the baseline condition, several participants moved close to the data to point at it.

6.3.3 Thinking physically about the data space

Two participants used physical descriptions of the data space. For example, one participant said: "Let me see what is out here", another: "I was in kind of a lane where I could filter instead of clicking with a mouse." That participant added: "It feels navigable," and considered that the way he had the attributes mapped to the floor space, he would be able to "Go to cars with large engines".

7 Discussion

We have explored opportunities for using body movement to interact with visualizations on large high-resolution displays and we have tested several of them. In particular, we have relied on the notion of proxemics [15] and a particular set of visualization tasks [18]. Overall, the three user studies provide initial data in support of the idea of using movement and distance to change visualizations. Participants in all studies said that using body movement was intuitive or natural.

Specifically, changing the visualization in response to changes in the user's distance to the display seemed useful. In Study #1, participants moved closer to the display for zooming in; in Study #2, participants moved closer to see data represented in higher detail ("more data in less space"). Changes to zoom level and representation made sense to several participants, maybe because it relates to the experience of physically zooming out and seeing less detail (due to visual acuity). In contrast, scaling views with user's distance worked contrary to the expectations of some participants (Study #3).

Based on observations and feedback from participants, potential benefits of proxemics-based zooming and aggregation are reduced effort and more smooth interaction compared to mouse control. Proxemics-based control also seems to allow navigation in or manipulation of many variables at a time in a natural way.

Another opportunity is the use of body movement for dynamic querying: In Study #3, we mapped the user's movement to selection of attribute values. One benefit observed for several participants, was that they could fix their focus on the data views while changing the selection by moving their body.

The studies also showed how using proxemics and visualizations together may give a distinct physical sense to abstract data. Study #3 differed from the other two in that movement was mapped to abstract data rather than spatial data. We note that the proxemics mappings used here did not directly reflect spatial relation between the user and the on-screen data range (as does Fig. 3), rather the data range was mapped onto the floor. The study revealed some interesting interactions nonetheless: You can step back to get an overview or walk to the left-hand side of the display to re-find previously seen details. The purpose of our empirical studies was not to provide detailed experimental data on the cognitive benefits of proxemics in visualization, but we think exploring this is important future work.

Our studies also suggested a need to get the fine details of interaction right. Participants needed a way of locking, both when using orientation and when using their body to change views: Leaning forward, close to the screen, could lock the screen. Such interactions could derive from more sophisticated proxemics data for distinguishing between relative poses of different parts of the body (e.g., shoulder relative to torso or hip) in addition to distance. Alternatively, users could have discrete zones for interacting through touch (close to the display) and for navigating through movement of the body (farther from the display). Also, proxemics-enhanced visualizations in our studies occasionally had unintended consequences: When participants in Study #3 moved to brush coordinated views, they sometimes changed the attribute unintentionally. Giving users more feedback on the sensed proxemics data might alleviate some of these problems. Vogel and Balakrishnan [52] also found that users were sometimes unsure about the exit threshold of a distance zone.

The idea of using proxemics for interacting with information on large displays is not new. Recent work has for instance demonstrated use of discrete distance zones for changing layout and representation of information [3,52]. The present work differs from previous work by explicitly relating proxemics to information visualization tasks; the studies demonstrate mapping of movement, orientation, and distance (continuous measures as well as discrete zones) to visualize, filter, sort, select, navigate, and coordinate tasks.

Also, whereas previous work has investigated mainly *static* visualizations on large high-resolution displays [2,8,55], the present research has investigated physical navigation for *interactive* visualizations, which presented new opportunities. For instance, Endert et al. showed that different encodings offer varying support for visual aggregation and thus impact the effectiveness of large-display visualizations [34]: "To support physical navigation, encodings need to have a balance between the expressiveness of glyphs and good visual aggregation properties." However, the findings from the present studies suggest that alternative designs are possible that allow users to benefit from different encodings at different distances and from more generally changing visualizations through movement.

Our studies suggest several avenues of future work; in particular we want to highlight three of these: (a) We have prototyped and evaluated uses of movement and distance for information visualization, but uses of other proxemics categories need to be explored in more depth, as well as combination of proxemics-driven interactions with other input (as already discussed above); (b) our aim was not to empirically understand the cognitive benefits of proxemics in visualization, this is important future work; (c) we have focused on single-user interaction, but proxemics may help us design visualizations for multiple users. To help doing so, future work should relate proxemics to research on collaborative visualization.

8 Conclusion

The present paper has presented findings from initial probing into proxemics-based interactions with visualizations. We intend to experiment further with combining proxemics-driven interactions and other input for information visualization; the studies presented here are intended to lend credibility to the hypothesis that it is useful (and even pleasant) to control and interact with visualizations using ones body movements.

Acknowledgments

(Removed for blind review)

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Paper III

F3: Fast, Fluid, and Flexible Data Exploration on Large and High-Resolution Touch Displays

Søren Knudsen and Kasper Hornbæk

Fig. 1. The photo in the figure's center shows domain experts using F3 to explore age distributions of patients admitted in relation to pregnancies. The photo shows: (1) they created an overview of treatments. (2) from this view, they explored treatment group 14, which relate to pregnancy and labor. This resulted in a view (not shown) showing different treatments of this group. (3) they reconfigured this view to show age distribution. (4) they explored the group of patients from 20 to 39 years, which resulted in another view. (5) they exploded this view by regions to understand how age compared across regions, resulting in the long view centered on the display in the photo, which shows that women in the capital region are older when they have children, compared to other regions.

The stylistic sketches to the left and right of the photo show two of F3's interactions techniques. The left sketch shows that dragging data fields from a menu and releasing them on the background, creates a view. The right sketch shows that dragging data bars from a view and releasing them on the background, creates a view drilled down on the data bar.

Abstract—While large, high-resolution displays with touch are becoming available, visualizations on such displays rarely use expressive gestures and abundant display space. This paper describes F3, a system tailored for data exploration with touch on large, high-resolution displays. The design of F3 was informed by inquiries with a group of domain experts that analyze healthcare data. The touch interactions let users create new visualizations and combine parts of existing visualizations. After introducing F3, we present two studies of the system. First, we evaluated the usability of F3 in a laboratory study. Results suggest that users were able to use F3 for data exploration and that they valued its ease of use. Second, we evaluated the utility of F3 for data exploration in a field study, where the group of domain experts used the system over two weeks. The field study shows that the domain experts could construct hypotheses, and generate and execute strategies quickly — supporting ad hoc discussions and question answering during meetings. These findings contrast domain experts' descriptions of hours of trial-and-error with their current tools.

Index Terms—Large high-resolution displays, interaction techniques, user study, visualization, lab study, field study, multi-touch

Introduction

Large, high-resolution displays with touch input capabilities are becoming widely available. Visualizations on such displays promise to advance collaboration on exploratory analysis of large data sets. However, we see two barriers to these improvements.

First, touch interaction for information visualization is just beginning to be explored [33]. Earlier work has shown how to integrate touch with specific visualization types (such as scatter plots [36], stacked area charts [4], node-link diagrams [15, 37], and bar charts [9]). However, these techniques are not tailored to create or combine visualizations using touch, nor do they support higher-level data exploration tasks with large data sets.

Second, few interaction techniques use the display space provided by large displays. While several studies have investigated how to support data exploration on large displays, and have outlined promising directions [29, 41, 43], studies that describe designs, implementations, and in particular evaluations of specific techniques are rare.

This paper introduces F3: a system designed based on long-term collaborations with a group of domain experts concerned with analysis of healthcare data. As part of this collaboration, we conducted contextual interviews and design workshops, which enabled us to design a set of interaction techniques inspired by this domain. The goal of the techniques were to ease collaborative exploration of large data sets by enabling creation and combination of visualizations (see Figure 1). We strived for techniques that are fast, in that actions have a short interaction time span, giving immediate reactions to interface actions rather than showing intermediary menus; fluid in that the system state is clear and prompt feedback is given on interaction choices; and flexible in that system elements can be combined and results obtained in many ways.

F3 provides touch interaction techniques for visualizations on large displays. The interaction techniques provide a novel approach to querying multi-dimensional data, and support drilling down, filtering, and grouping data. We base F3's interaction techniques on bar charts and use direct manipulation to interact with and combine database queries using visualizations of previous database query results through touch interactions. The techniques aim to provide freedom in choice of analysis strategy, which may benefit experienced analysts. F3 enables users to collaborate while constructing hypotheses, and generating and executing strategies quickly — supporting ad hoc discussions and question answering during meetings.

We contribute (i) a set of interaction techniques, that facilitate fast, fluid, and flexible collaborative data exploration using touch on large, high-resolution displays that were informed by design inquiries with domain experts and (ii) two complementary studies that show how the techniques support data exploration in the lab and in the field. These contributions help advance research on how to support data exploration on large displays, but also identify activities in data exploration that are not yet well supported in F3 or other systems.

1 Related work

We review three strands of research: (1) multidimensional data analysis, (2) visualizations on large displays, and (3) touch interaction with visualizations.

1.1 Multidimensional Data Analysis

Understanding large data sets frequently involves many visualizations and multidimensional data analysis. Dunne et al. [10] highlighted the importance of showing links between visualizations that leave a trail of visual breadcrumbs that represents their exploration. This supports users in understanding the actions that led to a visualization, recall the exploration history, and share analyses with others. Such trails provide a visual provenance of analysis results supporting users' analyses in a number of ways.

Stolte et al. described Polaris [39] (and later Tableau [45]) that facilitated exploratory data analysis through drag and drop of database schema fields. While they presented some interaction with the visualizations resulting from queries, they focused on constructing the queries, and only showed a single visualization at a time. Tableau has introduced possibilities for showing multiple visualization side by side, but does not support creation of a new a new visualization directly from the visual representation of an existing visualization.

Gratzl et al. [16] described a meta-visualization technique that allowed analysts to build visualizations that were based on smaller parts, which are connected with links, thus facilitating analysis of data relations through interaction. Elzen & van Wijk [13] presented a system that allowed analysts to produce overviews from detail views by selecting and aggregating data.

1.2 Visualizations Tailored for Large Displays

Information visualization on large, high-resolution displays has been the focus of several papers. Such displays allow for co-located collaboration, discussion, exploration, and analysis using information visualizations by providing a shared workspace with sufficient room for both individual and group work.

In visual analytics, large displays have been used to let users lay out and make sense of documents. Isenberg et al. [22] studied pairs collaborating on solving a puzzle using Cambiera, a collaborative text analytics tool for tabletops. Jacobsen & Hornbæk [26] replicated the study with a large, high-resolution display, Andrews et al. presented an array of displays for desktop use and suggested that they increase users' ability to carry out data analysis by giving "space to think" [2].

In information visualization, the focus has mainly been on single visualizations or multiple visualizations fixed at particular spatial positions [1]. To our knowledge, Lark [42] is the only system that provides free layout of visualizations on a large shared workspace. Lark used tree layout visualizations linked in a meta-visualization. The meta-visualization showed a visualization pipeline representation of the relations between the visualization views. Andrews et al. provided the Analyst's Workspace [3] that supported single-user sensemaking on a large display by automatically and with annotation showing links between related text documents. Singh et al. showed representations of analysis history for web log analysis on a large display [38]. Knudsen et al. [29] conducted a series of workshops with data analysts from diverse domains, and characterized links between visualizations that show analysis history and data processing as trails of thought, arguing these support backtracking and fluid exploration of alternatives.

1.3 Touch Interaction with Visualizations

Touch interaction with information visualizations has recently been called for [23, 33]. Such interactions may facilitate close-up work on large displays. Several papers have presented ways of using touch to interact with visualizations, but combinations of touch and large displays are still rare. Baur et al. [4] and Sadana et al. [36] contributed touch interaction techniques for stacked area charts and scatter plots, respectively. Rzeszotarski et al. [35] studied a physics-based approach to interacting with scatter plots. Schmidt et al. [37] and Frisch et al. [15] focused on touch (and pen) interaction techniques for node-link diagrams. These contributions focused on interaction techniques for a single visualization technique (i.e., stacked area chart, scatter plot or node-link diagram) and a single view.

Touch interactions may be used to facilitate data exploration by providing intuitive and effortless interaction techniques. Sketchvis [6] allowed users to create data-driven charts by drawing on an interactive whiteboard, supporting easy exploration of data. In a later study, Walny et al. [43] studied combinations of pen and touch input with Sketchvis. PanoramicData [44] used pen and touch interactions to support data analysis, using a whiteboard metaphor.

Kondo et al. [30] contributed touch interactions that facilitated navigation in time series with direct manipulation on parts of visualizations. Nandi et al. described gestures for performing database queries [34], focusing on interaction with database schemas, for example, to join two tables by dragging their columns together.

Drucker et al. [9] compared two sets of interaction techniques for bar chart interactions: gestural direct manipulation versus menu interaction. They discussed how the gestural interface guided participants with low experience with data analysis towards solving tasks, but at the same time limited more experienced participants.

1.4 Summary

The brief review of related work suggests two things:

First, we see a lack of work that integrates the benefits of touch, visualizations, and large displays. Collaborative data exploration could benefit from both abundant display space and dedicated techniques for manipulating visualizations with touch. We believe such benefits could be numerous, and have thus explored such possibilities through a series of design inquiries with domain experts. We are inspired by the techniques that GraphTrails used to show links between visualizations and Analyst's Workspace that showed links between documents. The simple drag and drop interactions demonstrated in Polaris and Tableau, and the effortless touch interactions in Sketchvis, inspired us to consider how this might work with touch interactions. Unlike GraphTrail, we show relations from data bars to other visualizations to help users understand data explorations in a collaborative context. A large workspace further facilitates collaboration and space to arrange many visualizations.

Second, we believe that support for data analysis tasks on large displays are too rarely empirically studied. After presenting F3, we report a laboratory and a field study of the use of F3's interaction techniques. We aim to consider a single set of interaction techniques and study them over a longer period of time.

2 F3: Fast, Fluid, and Flexible

We designed F3 based on a three-year collaboration with a group of domain experts, who perform analysis and documentation for a nation-wide healthcare organization comprising about 50 public hospitals, serving around 6 million citizens, and handling about 13 million patient contacts annually. We first describe the domain in depth to explain how the design of F3 was informed.

2.1 Domain Experts

To inform the design of F3, we conducted observations and contextual interviews over two weeks at the domain experts' site to obtain a thorough understanding of their tasks. We returned to the site for shorter day-visits throughout their work year to understand how their work changes in the course of a year. Their work reminds of tasks and work contexts characterized by Kandel et al. [27]. The domain experts level of expertise covers the *hackers* to *scripters* span.

The domain experts are about 10 employees, and part of a group of about 35 employees that work with documentation of healthcare services. They have mixed backgrounds, including economics, political science, mathematics, statistics, medicine, public health science, and computer science. They primarily use SAS, SQL, and MS Excel for data analysis. They use visualizations to understand data in Excel (e.g., bar charts, line charts, and scatterplots), and communicate data externally in static documents and with QlikView.

2.1.1 Domain Tasks and Data

The domain experts receive data from all national hospitals at regular intervals. The data is primarily used to compute rates for hospital treatments (diagnosis related groups [14]), which are based on matching hospital activities data to expenses. They publish these rates annually, enabling the government to use these rates as basis for compensating individual hospitals based on their workload. Figure 2 shows an overview of these collaborations and computation processes.

The received data comprise medical activities and financial accounts data. Medical activities data describe what has happened at a hospital (e.g., patient admittance and discharge dates from the wards and blood test meta-data from clinical biochemistry). Financial accounts data describe the expenses incurred at a hospital (e.g., doctor and nurse salary expenses for each hospital department, implant costs for each department, and overhead costs). To compute the rates, the domain experts establish the rate foundation table, which combines the medical activities and financial accounts data. The table contains a row for each patient (~13M/year). Each row describes a patient contact (an admission and discharge for inpatients and comparable information for outpatients), and comprise columns of patient information (e.g., age, gender, diagnoses), treatment information (e.g., procedures, duration, ward, hospital), and cost information (e.g., diagnosis related group, salaries, overhead). The domain data comprises for example: (i) codes describing operation procedures in a hierarchy of about 9.000 codes; (ii) hospital and ward definitions in another hierarchy of about 20.000 wards, that describe physical locations that change both name and id over the years; and finally (iii) admission and discharge times that would be expected to be within the two years covered in the database, in practice, spanned 44 years due to data registration errors.

The domain experts' work is characterized by constant adaptation to changing healthcare policies. This means that the data they handle change on a yearly basis. New information codes are added and existing codes may be changed or removed. Changes include addition of administrative patient pathway codes, combinations of codes describing in- and outpatients, and introductions of new medical procedures, thus requiring new description codes.

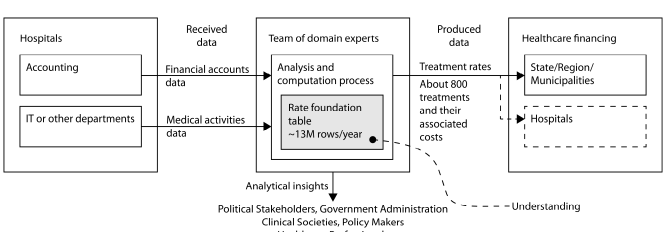

Fig. 2. The domain experts' collaborations and computation process.

2.1.2 Context of Work

The domain experts work in an informal work environment dominated by three- to four person offices. They frequently interrupt each other with quick questions such as *"do you remember the code for the new cancer treatment?"* Additionally, pairs of domain experts meet daily to weekly for scheduled one to two hour analysis meetings in front of a computer to work on a shared task. The domain experts also hold weekly group analysis meetings with their manager to discuss ongoing work. Current analysis meeting practice is, show data, ask questions, note questions, and go back to desk to analyze data after the meeting. When presenting analysis problems during such meetings, their manager might ask: *"but did you look into whether they all contain implants?"* which would require the domain experts to return to their desk after the meeting to answer the question.

The process of setting treatment rates involves communications with external political stakeholders such as clinical societies, policy makers, and regional healthcare professionals. Collaborating with these diverse groups requires communication of complex data to people who have limited experience with data analysis.

In addition to the yearly task of computing rates, the analysts solve smaller and shorter tasks to support internal and ministerial political functions, as well as researchers, journalists, and law enforcement, who share interest in obtaining knowledge from the data.

2.1.3 Design work

From these inquiries with the domain experts, we became interested in supporting parts of their work with quicker, collaborative, ad hoc data exploration tools. As part of designing F3, we conducted design workshops, and evaluated lo-fi prototypes and mock-ups with the domain experts. During our collaborations, the domain experts have worked creatively with us to come up with novel interactive visualization designs. We aimed to support tasks such as exploring why the number of patients admitted for specific treatments dropped from one year to the next and what the cost distributions of specific treatments across are hospitals.

Before using F3, the domain experts were accustomed to discussing data in meetings, and to looking at data in isolation. With F3, the goal was to let the domain experts discuss data while interacting, by enabling them to quickly and collaboratively construct hypotheses, and execute strategies, to support ad hoc discussions and immediate answers to questions about data during meetings.

2.2 Design Goals

The goals of F3's interaction techniques were to ease collaborative data exploration of large data sets by enabling fast, fluid, and flexible creation and combination of visualizations (see Figure 1).

F3's interaction techniques provide a novel approach to querying multi-dimensional data, and support drilling down, filtering, and grouping data. In designing the interaction techniques, the aim was to support data exploration by enabling fast, fluid, and flexible interactions on data:

Fast: User interface actions have a short interaction time span. In designing F3, we have aimed to provide immediate reactions to interface actions rather than intermediary menus. The argument is that it allows users to quickly gain overview of datasets and obtain valuable insights. In addition, data has been pre-computed, such that even complex queries return fast results.

Fluid: The user interface provides continuous feedback and invite for unbroken series of interaction. In designing F3, we have aimed to provide feedback on possible choices and the state of the system, and ensure that results of actions open the possibility for new system actions. This for example means that F3 gives feedback on possible release locations similar to tableau [45] when users drag user interface elements and that it is possible to interact with many parts of visualizations.

Flexible: The order and approach to data exploration is flexible. In designing F3, we have aimed to create interaction techniques that allow for variation in data exploration. For example, there are many possibilities and ways of combining user interface elements to produce different outcomes, and that the same analysis goal can be achieved in several ways.

We aimed to provide interaction techniques that support data discovery, exploration, and comparison (why's in [5]). We did this primarily by enabling the low-level selection, navigation, arrangement, filtration, and aggregation visualization tasks (a subset of manipulation how's in [5]). In designing F3, we wanted visualization components and data fields to be able to be touched and dragged onto as many elements in the user interface as possible.

We designed the interaction techniques with inspiration from design guidelines for post-WIMP user interfaces [12, 33] (e.g., consider feedback, reduce indirection, and integrate UI components in visual representations). We also aimed to enable users to use both hands in a single task (e.g., to select an item as context for another, see [18]), or in simultaneous tasks (e.g., do two similar actions at once).

The interaction techniques in F3 can be adapted to many visualization techniques. For F3, we chose to focus on bar charts. The domain experts that we have designed F3 for, are familiar with bar charts, and use these often. Additionally, bar charts display aggregate information, and therefore apply well to the visualized domain data.

2.3 Data Model

We have designed F3 primarily to help the domain experts understand the rate foundation table and its potential data errors. The rate foundation table is multi-dimensional and contains highly hierarchical data. Constructing an OLAP cube [17] based on the rate foundation table, facilitates slicing, drilling down, and pivoting according to any of the tables' columns to enable detailed data exploration and analysis.

We based F3's visualization and interaction techniques on the data cube model. This helped facilitate meaningful results from combinations of user interface elements. The core parts of the model consist of *dimensions*, *levels*, *members,* and *measures*.

Nominal data columns in a data table often map to *dimensions*. For example, year, month, and day columns often map to a date dimension. These are *levels* of the date dimension hierarchy, and instances of these levels are *members*. For example, a date dimension may contain year as a level, which contains 2013 as a member. F3 encodes dimensions with data bars' horizontal position in bar charts.

Quantitative data columns in a data table often map to a *measure*. For example, cost often map to a measure. Measures contain aggregates of raw data columns, grouped by dimensions. F3 encodes measures with data bars' height in bar chart.

To be able to construct histograms, it is useful to bin some measures, for example to construct a histogram of costs. Therefore, the data model can contain data fields, which are possible to use as both measures and dimensions. We refer to these as binned measures.

3 Interaction Techniques in F3

The interaction techniques in F3 support creating visualization views by combining, extending, or re-using existing visualizations. In doing so, the techniques provide a novel approach to querying multi-dimensional data and receiving visualization views as query results. Table 1 present an overview of the techniques; Figures 3 to 9 show them as sketches to improve readability. The first techniques are simple but necessary for exploring data; the latter techniques are more complex and aim to help solve specific tasks. Next, we describe the basics of each technique, discuss design alternatives, and open issues.

3.1 F3 Interaction Concept

In F3, access to data happens through a data field menu in the top part of the display (see Figure 1). The menu shows dimensions and measures from the data cube model [17]. Users drag data fields from the menu and drop them on relevant parts of the user interface.

We opted to use a statically positioned data field menu as initial entry point. As an alternative, we considered showing a menu when touching relevant parts of the user interface, but imagined that the chosen solution requires fewer instructions to get started, and thus work better for walk-up use.

Views are the main user interface element of F3. A view shows data in bar charts. The x-axis encodes dimensions and the y-axis encodes measures. Users move views by dragging with one finger.

To create a view, users drag a data field from the data field menu and release it on the canvas (the background area), which results in a bar chart that shows the dropped data field (see Figure 1). We designed view creation with focus on speed and of ease of use, since creating a view is a necessary first step in most tasks, and thus frequently used. Because the dragged data field may both represent a dimension and a measure, the two possibilities provide slightly different results. A dragged dimension or binned measure results in a view that encodes the dragged field on the x-axis, whereas a dragged measure results in a view that encodes the dragged field on the y-axis. The axis not mapped by the released data field shows a default data field provided by the data model, which for the y-axis could be number of observations in the database. After creating the view, users may reconfigure views axes, which the technique described next facilitates.

3.2 View Configuration

To *configure* a view's axis, users drag data fields from the data field menu and release them on a view's axis label. This allows users to perform the most essential configurations of a view. It is possible to drop dimensions on x-axes, and measures on y-axes (see Figure 3). Dragging a data field over an axis highlights the release area, if the dragged field is compatible with the axis. Dropping the data field configures the axis. This provides users the opportunity to alter views as needed, and to select alternatives to the default selection.

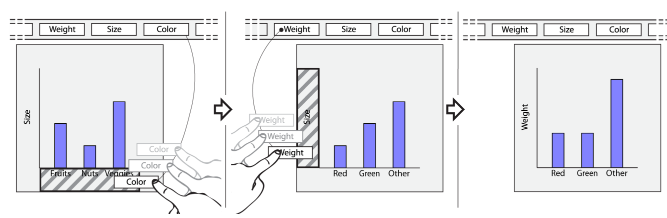

Fig. 3. Drag data fields onto view axes to reconfigure views.

3.3 View Cloning

To create a clone, users drag a view with two fingers (see Figure 4). This allows users to continue their exploration in a clone, for example

Interaction Technique	Action	Result	Complexity
View Creation	Drop a data field on the canvas	A new view	Simple
View Configuration	Drop a data field on a view's axis	The view's axis is re-configured	Simple
View Cloning	Drag a view with two fingers	A clone of the view	Simple
View Synchronization	Drag views so that they overlap, then tap button	Y-axes in the two views use the same scale	Simple
View Exploration	Drop a data bar on the canvas	A view drilled down on the data bar	Complex
View Filtration	Drop a data bar on a view's filter area	The view is filtered based on the data bar	Complex
View Exploding	Drop a data field on a view's explode area	Views for each of the data field's members	Complex
Trail Cloning	Hold data bar, while clone dragging a child view	A clone of the trail between data bar and view	Complex
View Matrix creation	Drag views so that their corners overlap	A matrix of views combining the views' axes	Complex

by changing axis encoding, while the original view is preserved. We designed cloning to work similar to drag, and leverage the added efficiency provided by chunking [7] drag and clone interactions. To rearrange a view and create a clone, users start by dragging a view. Adding a second finger after positioning the original view, results in a clone operation. The user is then free to use one or two fingers to continue positioning the clone view.

F3 reserves two-finger and two-hand interactions for more advanced and infrequent interactions. We designed view cloning for single hand two-finger operation.

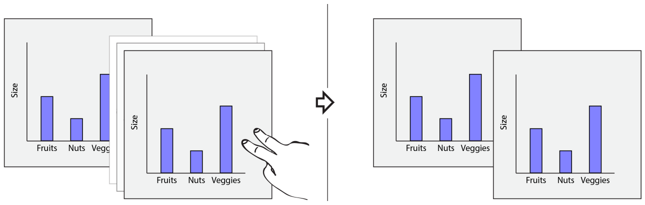

Fig. 4. Drag views with two fingers to clone views.

3.4 View Synchronization

To *synchronize* views' y-axis scales, users drag a view such that its side area overlap another views' side area (see Figure 5). This helps users to compare views. When views that encode the same measure overlap, a synchronize button appears above the y-axes in both views. While holding onto the view, tapping the synchronize buttons with a finger from the other hand, cause the view in which the button was tapped to adopt the scale of the other view.

We designed the technique with the aim to reduce unintentional synchronizations while for example arranging views and to keep the design of the technique similar to the other techniques. We also considered if the technique should facilitate measure changes, but chose not to, to reduce chances of errors.

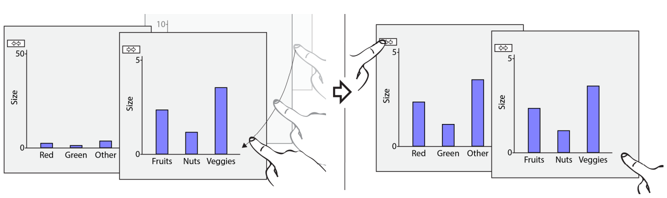

Fig. 5. Drag views onto each other so that they overlap. A synchronize button to appears. Tapping it synchronizes the axes'

3.5 View Exploration

To create a child view based on data represented by the parent data bar, users drag data bars out of a view and release them on the canvas (see Figure 1). This allows users to drill down and perform more detailed data exploration in a new view. The metadata necessary to provide a useful result is obtained from the data model that provides *child members* (e.g., 2014, September, or 22nd) at a *level* below the data bar (e.g., year, month, or day). F3 show these child members on the x-axis in the child view. In case no child members exist for the dragged member, the child view shows the dragged member.

To add additional data bars' child members to the child view, users drag these bars from the parent view and release them on the child's filter area, which is located above the data area. This allows users to select multiple items from a view to analyze in more detail. To show how the child view was created, a line represents the parent-child relation from the parent data bar to the child views' filter area.

Creating a series of views, in which each child is the parent of another child, shows a history of exploration steps, which has been referred to as a trail of thoughts [10, 29]. F3's parent-child representation does not rely on color encoding, thus freeing color encoding for other purposes. At the other end of the design spectrum, color highlighting could completely replace the use of line

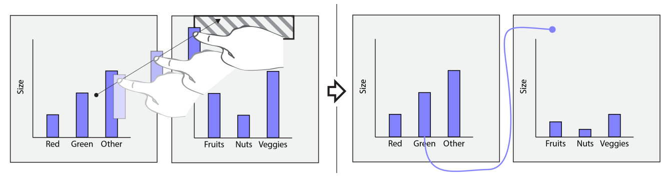

Fig. 6. Drag data bars onto a views' filter area, to filter by the dragged data bar.

connections, which might be sufficient as long as there are relatively few views. Since the aim of F3 is to support numerous views, it is necessary to use line connections to represent parent-child relations.

3.6 View Filtration

To filter data shown in a view, users drag data bars out of a view and release them on another, yet unrelated, views' filter area (see Figure 6). The technique is similar to view exploration, and allows using views as filter palettes, supporting flexible exploration in other views. When users drag data bars to the filter area, it is highlighted. Multiple filters on a dimension are represented as a single circle and are logically OR'ed. Filters on different dimensions are represented as different circles and are logically AND'ed. Because the design does not include range-queries, it is useless for two filters on the same dimension to be OR'ed. Flicking up or down on a filter circle inverts the filter. Similarly, flicking left and right on the filter circle enables or disables the filter (this also works for *view exploration*).

3.7 View Exploding

To explode a view according to members of a data field, users drag data fields from the data field menu, and release them on a view's right-hand side (see Figure 7). This facilitates breaking down the original view by the dragged data field and comparing its different members to each other, similar to small multiples. The explode area is highlighted when dragging data fields on top of it. Releasing the data field generates views for each member of the dimension. The abundant display space allows view multiples of similar size and scale to the original view, which facilitates comparison.

The result of the technique is that the original view's border area increases, such that it contains the original view, as well as the member views to the right of the original view. F3 shows members in a scrollable list if there are more than four members. F3 aggregates the members that scrolling hides, in a view to the right of the list.

Data bars from other views may be dropped on the explode area, just like data fields, to explode the view by child members of the aggregate represented by the bar. For example, dropping the data bar 2013 on the explode area, generates views filtered on quarters of 2013.

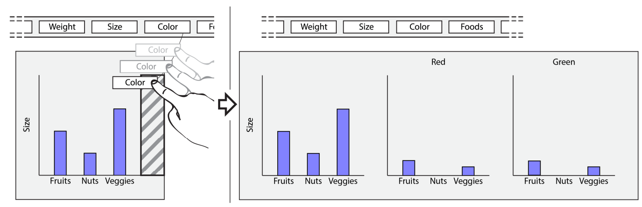

Fig. 7. Drop data fields on views to create copies of the view, filtered for values of the dropped field.

3.8 Trail Cloning

To clone an entire exploration trail, users hold onto a data bar in a parent view, while dragging a view using two fingers similar to cloning a view (see Figure 8). This facilitates comparisons between subsets of data, which may be useful, for example, when a user look at one part of data, and would like to see if other parts show similar patterns. When holding onto a views' data bar, F3 highlights trails of the view that users can clone. This sets the context for the following interactions. Using the other hand, two-finger dragging a highlighted view creates a clone trail. This results in a new exploration trail showing views similar to those in the original trail, and facilitates fast and fluid comparison between the two sets of data, in that the new trail can be created quickly, and that it is possible to perform the interaction as part of a longer series of interactions. F3 positions the cloned trail where users released the dragged view, and lays out intermediate views similar to the original views, which the right side of Figure 8 shows. F3 allows creating trail clones when all members between the data bar held on to and a child view exist in the potential cloned trail.

The abundant display space provides the opportunity of showing many views. Trail cloning provides a fast way of creating them. In particular, the technique facilitates comparison between multiple comparable slices of data, which is a common data analysis task [4].

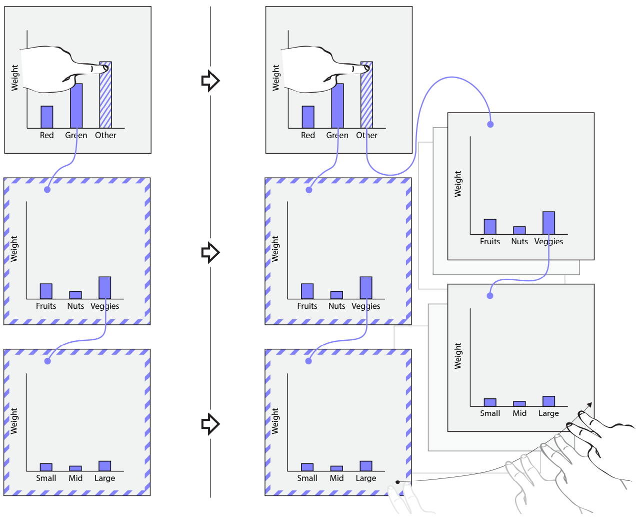

Fig. 8. Trail cloning technique: An exploration trail can be cloned by holding onto a data bar in a parent view, while two-finger dragging a child view.

3.9 View Matrix Creation

To create a view matrix of the combination of two views, users drag one views' corner on top of another views' corner (see Figure 9). This allows users to relate and compare data in the original views. When a user drags the top-left corner of one view on top of the bottom-right corner of another view, F3 shows view matrix creation is possible by highlighting the views' corners. When the user releases the view, F3 creates a matrix combining the two views' dimensions and measures. The source views keep their approximate position within the matrix.

The number of rows and columns in the matrix depend on the dimensions and measures in the two source views. Dimensions that have no corresponding measure (e.g., fruit or hospitals), only fit on x-axes, and thus only on matrix columns. Likewise, unbinned measures only fit on y-axes, and thus only on matrix rows. F3 creates a 2x2 matrix if users combine views that encode such data fields. In the other extreme, F3 creates a 4x4 matrix if users combine views in which both axes in both views encode binned measures.

If the two views encode the same dimension and level on the x-axis or the same measure on the y-axis, then the views are incompatible and *view matrix creation* is not possible. If the two views are incompatible, F3 does not highlight the views' corners when users drag the views onto each other.

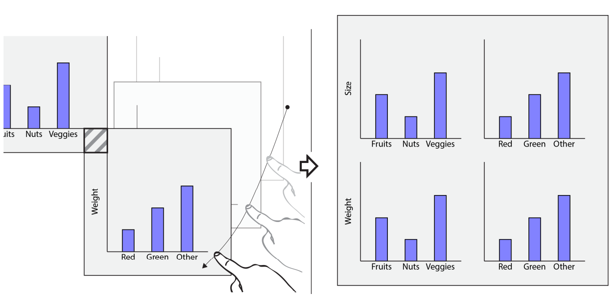

Fig. 9. Drag view corners over each other to create a view matrix.

4 Implementation and Apparatus

We implemented F3 in Java using a combination MT4J [32] and the Prefuse data visualization toolkit [20]. Specifically, the Prefuse renderers where ported to MT4J where they generate and update MT4J components. The data and data model were stored in an MSSQL server and MSSQL Analysis Services cube respectively. F3 query the data using Olap4J (www.olap4j.org).

F3 can be used on different display sizes and touch systems. However, we conducted both studies in the following on a Smart 8084i display shown in Figure 1. This display has a spatial resolution of 3840x2160 (also known as 4k), a 30Hz refresh rate, measures 84 inches diagonally and supports 4 simultaneous touch points. An 84" display is sufficiently large to provide the experience of abundant display space, while still physically possible to move into busy offices and employees' work area, which was necessary for the two studies described next.

5 Study #1: Formative Laboratory Study

The first study investigated usability issues and reactions from participants whom we asked to solve a range of data analysis tasks.

5.1 Participants, Data and Tasks

We recruited nine participants (age: 27-57, mean 34). Participants were current or former Master-level students. They all conducted data analysis on a regular basis.

We used the rate foundation table that comprised nation-wide admissions, treatments, and expenses data for the years 2012 and 2013 as basis for the data cube that spanned 7 dimensions and 6 measures.

The tasks were developed from taxonomies of data analysis [5] and inquiries with domain experts (see section 2.1). The first four tasks were brief and asked participants to answer factual information (e.g., "how many patients were admitted to hospital X", "How many 11 year olds were admitted across the dataset"). The next two tasks were longer and required several interaction steps (e.g., "How many patients aged 65 or more has received plastic surgery at hospital X"). The last two defined tasks were complex tasks that required for example data comparisons (e.g., "Which treatments are cheaper on large hospitals than on small hospitals in the capital region"). We deliberately asked participants to work on clearly defined tasks, even though the goal of F3 was to support data exploration. We chose this approach because the goal of the study was to ensure that the system was useful before deploying it in a field study.

5.2 Procedure

During the session, besides the participant, we were two persons present in the room, engaged in a facilitator and an observer role. The facilitator's role was to keep the session on track and the participant at ease. The observer's role was to observe and take notes. Both were allowed to ask questions.

First, we asked participants to use the system, and to explore the interaction techniques. To assure participants understood and used the entire range of interaction techniques, we observed them closely in this phase and gave suggestions about what to try if they were in doubt. We encouraged participants to ask questions throughout the session.

After we introduced participants to F3, we asked them to work with the tasks described above, one by one. We administered the tasks in writing. If time permitted, the facilitator and observer asked questions, before moving onto the next task. Finally, if time permitted, we asked participants, to define a task on their own, and to solve it using F3.

At the end of the session, we interviewed participants about their experience with the system and interactions, including its benefits and drawbacks compared to other systems they knew, and followed up on aspects of their interactions or what they said during the session.

The sessions lasted between 55 and 65 minutes.

5.3 Data Collection and Analysis

Participants were video recorded, and the facilitator and observer kept notes of usability issues and participants' utterances. We also used the notes as basis for the interview described above.

We analyzed the collected data in four analysis sessions based on the Instant Data Analysis technique [28]. The analysis sessions, which we conducted within a day after participant sessions, lasted on average one hour. For the analysis, we gathered in front of a whiteboard. We transferred observations to sticky notes, fixed them to a whiteboard, and presented and discussed our observations. We then categorized the sticky notes into themes and clustered them on the whiteboard. Based on the clusters, we captured the most important findings with references to the observations and any supporting video recordings.

5.4 Results

First, we describe which techniques participants used. Then we present the results in terms of five topics that we observed across several participants.

5.4.1 Use of F3's Interaction Techniques

All nine participants understood and used view creation, configuration, cloning, and exploration. Many participants seemed uncertain about the effects of the other techniques, even after we guided them through using them. Only one participant actively used view matrix creation and no one used trail cloning.

One participant quickly understood how view cloning would enable him to try out new approaches and strategies, which enabled him to perform a range of analyses in a rapid manner.

5.4.2 Drilling Too Deep

Seven out of nine participants *drilled too deep*. While reading off the value of a data bar might solve a task, participants instead dragged the data bar out of the view, thus creating a new view drilled down in the aggregate. This did not give them the answer to the task. Some participants merely stopped looking at or explicitly closed the child view, and read it from the parent view as required, while other participants got confused and either stopped to consider what to do, or alternatively, tried to manually aggregate data in the child view.

Participants found F3 backwards when they wanted to isolate a member from one view in another view, aggregated by another dimension. F3 lets users do that by dragging out the data bar, (i.e., drilling), and then configuring the view with the needed dimension. For example, if participants needed to see a view filtered on a single hospital, they often created of view of hospitals, and then dragged out the wanted hospital. This resulted in a drill-down on hospital, thus creating a view of wards on the chosen hospital. To see other aspects of the hospital, participants had to drag another dimension onto the x-axis, which they seemed to either not remember or understand.

5.4.3 Combinations of User Interface Parts

Some participants were unsure about possible combinations of user interface parts. They had understood that it was possible to combine many elements, but it was unclear to participants, which particular elements that it was possible to combine. Consequently, participants tried to combine elements in ways that we had neither considered nor implemented. One participant, for example, tried to drag two data bars together, which F3 does not support. When we asked the participant what she expected the result of the action to be, she suggested that it might show both data bars in a view. Two participants also tried to drag a view to another views' explode area, which they seemed to expect to result in exploding the view by data bars in the dragged view.

It seemed that some participants did not consider what they were dragging, but only where they dropped it. For example, a participant dragged a data bar over many parts of the user interface while thinking, reminding of Dwyer et al.'s "thinking with their hands" [11].

5.4.4 Default Axes

Default axis selection seemed to create some confusion when participants had created views. It seemed they were not aware of the default choice, but only realized it when they needed to solve a task that required them to select another measure.

5.4.5 Data Exploration

Two participants suggested that F3 would be a good tool for exploring data. A participant that had obtained a particularly good grasp of the different possibilities considered two ways a data exploration could progress: He could create consecutive child views by drilling and reconfiguring, for example to see data for people above 65 that had plastic surgery performed at a specific hospital. This would leave a trail of the exploration process. Alternatively, he suggested to creating three views that showed age groups, treatment types, and hospitals. He would then drill on one of these views, and later filter the resulting view using the other views. The result would be identical, but the process of getting there, and the layout and relations between views, would be radically different.

In contrast to this, a participant said that she was used to seeing more information in a single view. She thought it weird with so little information in each view, but so many views. In addition, this participant suggested that the system was too visual, and that she would rather conduct her analyses by programming and looking at data tables (which repeats findings in [27]).

5.4.6 Experience

Many participants found F3 useful and efficient, in spite of their confusion. Two participants said that F3 provided playful interactions. In the debriefing, they explained how they would analyze their own data with F3. One participant described F3 as *"simple charts, fast"*. Another participant emphasized the speed at which she was able to conduct analyses with F3. On her way out the door, one participant said "*bye, bye. It was fun to play…",* which stressed the experience that she had had with the system. In contrast, a participant that had many problems using F3 said he "*lacked the appetite"* for using it.

6 Study #2: Field Study

Where the first study sought to evaluate the usability of the interaction techniques, the second study focused on how the domain experts described in section 2.1 would use the interaction techniques as an integral part of their work. The study aimed to understand how F3 support data analysis tasks that span hours or perhaps days and that involve data exploration. We based the study on real data and tasks that potentially involved many analysts. The duration of this study allowed us to understand the benefits of one technique over another, and to understand how analysts can use techniques creatively to explore data, uncover new understanding, and gain insight.

6.1 Deployment

We deployed the 84" display and F3 in the offices where the analysts worked during two regular workweeks. Initially, we installed the display in an office shared by two employees and an external consultant (first location). After four workdays, we moved the display to a small room that was regularly used for impromptu stand-up meetings and that more people passed by during the workday (second location). Aside from the display, there were two tall café tables in the room. In this location, a more varied group of people used F3. Moving the display created new interest, even from those had been sitting near the first location. The display remained in this location for the remaining six workdays. During the entire period, we expect that about 20 people have interacted with the system, and that a group of 6 domain experts have used the system for more than half of the time. In total, 907 views were created comprising all F3's techniques.

6.2 Data Collection

To obtain a satisfying understanding of how the analysts used the display during the deployment, we based data collection on triangulation: We logged user interactions, captured screenshots at 5-second intervals, and recorded audio during system use. In addition, we visited the deployment site at least once every day for one to six hours to make sure the system was being used, to observe the use, to conduct interviews, and to resolve technical problems. We kept field notes while on-site. Immediately after leaving the site, we logged short audio memos describing our observations from the visit. Inquiries with the team of domain experts over the past three years provided further context to understand the techniques' use in the broader context of their work. In addition, we used the visits to gather requests for features or updates to the data model. These requests were actively encouraged, to create pull from the analysts. Finally, we conducted interviews with three key analysts at the end of the deployment period.

6.3 Making Sense of the Collected Data

Analysis was informed by Grounded Theory [40], advocated for InfoVis in e.g., [8, 24]. We continuously moved from the field to the data and back again, reformulating our coding and questions, thereby gaining understanding of the way the analysts used F3. The collection and analysis of data also served to address deployment issues.

At the end of the deployment, we gathered all data to obtain an overview: We transcribed observation audio memos, and along with notes from interviews and observations transferred these to sticky notes to facilitate affinity diagramming. We only use interaction logs to describe the extent of F3's use during the deployment, because the logs contained noise caused by our presence on-site in terms of suggestions to the domain experts for what to try and our own interactions with the system. We used the sticky notes as entry points for further analyses of screenshots and audio recordings to provide additional detail when necessary. Some notes specifically suggested returning to the audio material to obtain greater insight, which resulted in adding new sticky notes to the affinity diagram. The final part of analysis condensed seven themes, which we describe next.

6.4 Field Study Results

We present the results in terms of seven themes.

6.4.1 Use of Display Space

The entire display was used to lay out views, although the left-center was used first and most. Views were never positioned such that they extended towards the top border. A few views extended the left or right border, such that most of the view remained visible. On one occasion, the domain experts positioned views extending below the display, to store unused views.

6.4.2 Interaction Techniques and Data Model

During the two weeks of deployment, the domain experts requested many additional features from F3. We logged feature requests, but chose not to provide any of them, which would potentially alter the system dramatically. The most common requests were to provide view scaling to show more data bars in a view and provide additional visualization techniques (e.g., scatterplots). The domain experts also frequently asked for general process and provenance [21] support in F3 (e.g., annotate, record, share, desktop integration). More rare requests centered on the visualization and interaction techniques provided by F3. The domain experts wanted visualizations to: show several measures in bar charts next to each other; to allow analytical abstractions (e.g., show the difference of two views); and to show stacked bar charts. The domain experts asked for interaction that focused on views. For example, to be able to undo actions, drill-up and down, and filter, all within a single view. Aside from within-view interactions, the domain experts wanted to be able to create a new view with a single data member (i.e., a filter) by dropping a dragged data bar on the canvas similar to view exploration, but without drilling, to be able to select a few aggregates to continue exploring. This shows that what normally was an effective technique, seemed to limit participants in some circumstances. A domain expert described the difficulty in removing a single member from a view. We designed F3 to show all filters explicitly through view relations. We therefore chose not to provide a simple technique for this. Instead, F3 can use view exploration, followed by inverting the relation. Although this solution is more complicated that what the domain experts asked for, it helps to understand the filters applied to data.

The domain experts requested many updates to the data model. For example, we added 14 new dimensions, ending in 21 dimensions. These requests illustrates the domain experts' motivation for using the system – they were eager to use F3, and use it for more than they could without updates to the data model.

6.4.3 Exploration of Data

Quick insights: After an analyst had discovered what seemed to be an important data error in a matter of seconds with F3, he estimated that it would take 30 minutes to conduct a similar exploration with their current practice. When asked to compare the current analysis practice to using F3, he said *"[F3] is more playful, the leap from thought to action and result is shorter"*, and that "*there are fewer steps involved"*. When F3 crashed (which it did on occasion), he said that he *"was forced to remember what he had done"* which showed that, although the fast and fluid properties had helped him to perform analyses quickly, remembering what he had done was difficult. F3 would have helped him in this regard by showing views' relations, but when it crashed, it was clearly demonstrated the support given by showing those relations. This shows that he used F3, without thinking consciously about how he approached the exploration. He also stated that, *"our current practice also leaves more flexibility [in terms of how we can perform analyses]"*. Another analyst described working with F3 as *"impromptu analyses in data"*. She described F3 as quick to provide results, as visual (as opposed to looking at tables in SAS), and as flexible, in that dimensions and measures can be the combined simply by drag and drop.

Problematically playful: The playful quality was problematic in some circumstances. In some analyses, it was clear that analysts were too fast, without keeping their goal in mind, and drilled too deep (as in study #1) into a slice of the data set. It seems that keeping a mental overview, while playing and exploring the data was problematic for the analysts. One analyst thought that it was *"a bit harder to keep the overview, because it is so easy to drag something new in, whereas if we are programming it, we typically plan what we want to do beforehand. Here, you typically drag something to see: how does that look? Is it something to proceed with, and otherwise you close and continue"*.

Difference to current practice: The analysts described the difference between their current practice and using F3 in terms of how they find errors in data: *"You don't sit and play with the data. Most often, you're looking for something specific."* This showed that the fast and fluid properties of F3 provided the analysts with new possibilities for exploring data, and find anomalies or errors, that they were unable to find easily otherwise. Another analyst further commented that seeing the context of a task with more data was useful, and increased her awareness of the task. The analysts liked how F3 helped constructing new hypotheses in their analysis by supporting exploration of data. One analyst said: "*[F3] is good for getting ideas. Ideas that should be looked into"*. Here, ideas covered data errors and other things that should be corrected.

6.4.4 Visualizations of Data and Relations

The analysts liked that F3 showed data visually, but also commented that they were not used to see data that way (the analysts primarily use data table representations when looking at data). An analyst said that she had to *"get used to seeing data visually"* – which she described was hard for her. At least five analysts repeated this sentiment in various forms. They did see the value in the visualizations, but some also used the textual representations of aggregate values that F3 showed when tapping a data bar. This seemed to reduce misreading visualizations, for example by facilitating a sanity check for scaling similarity in compared views.

The analysts liked the way that F3 visualizes the relations between views. One analyst for example said: *"I can obtain an overview of how the views are created".* We suspect that these representations helped participants understand F3's feedback during interaction, but have no empirical evidence for this.

6.4.5 Views as Toolboxes

In F3, we noticed that some participants used views as tools. We call these *toolbox views*. They are views that users create, only to be able to drag data from the views to filter other views, which have the users' focus. Toolbox views bring little value except for helping other exploration steps. The ability to use toolbox views in F3 is unique, in that auxiliary views make use of the abundant display space. With less display space, using toolbox views would seem like wasting pixels.

A domain expert that was quick to grasp the idea of using views as tools said: *"You just have to turn it up-side down in your mind".* Most of the other domain experts seemed to find it difficult to use views as a tool in exploration, and seemed to forget the approach. However, as one analysts said: *"If you are looking into a specific problem, seeing the context is important".* In this statement, the context was a view, and the object of interest a data bar dragged from the view.

6.4.6 Collaboration

The domain experts considered using F3 in collaborations with peers on-site. They experienced such collaborations during the deployment and thus considered how F3 could become a permanent part of their work. For example, an analyst said that using the display during analysis meetings would facilitate answering of open questions straight away during meetings, supported by F3's simple and fast interactions. In contrast, current analysis meeting practice is to show data, ask questions, note questions, and finally analyze data after the meeting, as outlined in section 2.1. This suggests F3's value in internal collaboration. The analysts also described how F3 invited for discussions about data. One analyst said that collaboration between several analysts helped generate analyses and ideas, and that it was easier, more fun, and less error prone than doing it alone.

The analysts also frequently considered using F3 for communications with external collaborators such as clinical societies, policy makers, and regional healthcare professionals. For example, when two analysts showed F3 to a group of collaborators from a university hospital, they collaboratively discovered a data error. An analyst suggested that F3 could improve the process of collaborating with clinical societies. She imagined that instead of endless series of meetings and email exchanges that take the form of negotiations, using F3 could facilitate collaboration, increase mutual understanding of complex issues, and help to arrive at conclusions faster.

6.4.7 The Domain Experts Obtained New Insights

During the study, the domain experts found three potential data errors, which they added to a list of concerns. According to the domain experts, this was much more than expected. For example, they discovered that the average amount of bed days for a region was four times higher than other regions. They hypothesized that the region had conducted incorrect registrations, conducted registrations according to an old standard, or that an internal process had failed to remove parts of data that were irrelevant for later analysis. We inquired if and how finding the potential data problems was due to F3. The reasons most often attributed to finding errors, was the speed of data exploration with F3, and that they could collaborate efficiently in the process.

7 Discussion and Conclusion

We have presented F3, a system implementing a selection of interaction techniques that (a) use touch to create and combine visualizations and (b) work well with abundant display space. Next, we discuss the interaction techniques in F3, the two complementary empirical studies of F3, and limitations/future work.

7.1 Benefits of Interaction Techniques in F3

In designing F3, we wanted to enable users to touch, drag and drop as many visualization elements and data fields in the user interface as possible. Participants liked being able to drag things out of views and generate new views. Our studies suggest that this could be due to the direct mapping between what they saw, what they did, the reaction they obtained, and how F3 represented this visually with links. We believe this a key strength of the interaction techniques used F3. However, we also observed some participants' uncertainty about component mappings in study #1, which later inquiry confirmed. There are two takeaways from this: First, participants formed conceptual models of where data fields and aggregates could be dropped, and assumed that other parts of the interface worked similarly. A guessability study may provide the necessary information about the additional possibilities for a redesign. Second, the feedback provided by F3 should be improved to give more clear information of where data fields and aggregates could be dropped.

We believe F3 allows users to create many views easily, thereby making use of the abundant display space. While this follows suggestions from earlier work (e.g., [29]), we argue that several of the interaction techniques in F3 are novel in this regard. The empirical work suggests that some of the interaction techniques (e.g., view cloning, exploration, filtering, and exploding) were easy to understand and useful. These techniques helped participants think and execute complex data explorations quickly, some of which took hours of trial-and-error in their current system. While some of these would have benefitted from any kind of visualization, we think that the aggressive creation and expansion of visualizations in F3 is the key benefit.

7.2 Empirical Studies of F3

The results of the studies suggest that users were able to use the techniques to perform data exploration and found them useful. We can think of only few studies showing such findings in a field study.

The laboratory study identified design concerns such as too much drilling, which largely were unimportant in the second study. One reason for this was that the analysts in the second study had much longer time to learn to use F3, and to apply the techniques to perform data exploration as part of solving their overall analysis tasks.

We want to discuss briefly our choice of methods. Empirical work is scarce in the related work. At least a part of this reason is that large, high-resolution touch displays has only recently become available. Another reason for the lack of empirical work is that it is difficult to establish good collaborations with experts that may use visualization systems. In addition, information visualization research has only in the last decade begun to use empirical studies as a crucial evaluation method [25, 31].

We acknowledge that it is difficult to separate the effects of the specific system (F3) from the general technology (large display visualizations) in field studies such as the reported. However, we believe that the field study showed that F3 enables collaborative data exploration in a manner and efficiency that other systems do not support. For example shown by the fact that external collaborators were able to take part in exploring data with F3.

7.3 Limitations and Future Work

F3 is limited by supporting only bar charts; we prioritized instead to make it work with large-scale data that could be used in a field setting. Support for alternative views was a common request from participants in both studies. Many of the interaction techniques can easily be applied to other visualization techniques, for which there are plentiful [19]. Some of the interaction techniques may well be more useful with other visual representations. View matrix creation, for example, creates matrices, and scatterplot matrices have been shown to be extremely valuable for some tasks. Selections in scatterplots may also be designed such that they facilitate dragging them out of a view, to isolate in another (e.g., like selections in [36]).

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Paper IV

Representing View Relations: A Qualitative Study on Between-View Meta-Visualizations

Søren Knudsen and Sheelagh Carpendale

Abstract— To improve our understanding of the use of meta-visualizations to help explain view relations, we conducted a qualitative study in which we invited people with experience in both visualization and interaction design to work with, discuss and sketch representations of view relations. Because data analysis based on visualizations frequently involves creating and navigating many visualization views, it is becoming important to develop ways to keep track of how one visualization view relates to another. The pressure to find effective solutions for representing the relations between views is being fueled by the increasing prevalence of large, high-resolution displays, which provide more space for multiple views and view organization. However, the simple increase in display size does not inherently provide the additional analysis support that may be needed. Between-view meta-visualizations may help to address this need by offering methods that can reveal relations between views. Through our exploration of the possibilities for showing between-view relations, we discovered several factors such as the data itself, the parts of the data that are shown, the flow of data, the encoding of the data, the view coordination, and the interactions that can be used as part of meta-visualization representations. Our results, together with existing research, form the basis of a six dimensional framework that expands the range of possibilities of between-view meta-visualizations.

Index Terms—Large displays, visualization, multiple visualization views, multiple coordinated views, interaction techniques, qualitative study, view relation, meta-visualization

Introduction

As visualization research expands, and the demand from analysts for effective visualizations increases, visualizations that offer multiple views have become more and more common. Now that large displays that can facilitate simultaneous display of several views are more readily available, there is even more pressure to support view coordination. This has been a common theme in visualization research. Workshops have been held on multiple coordinated views (MCV) [22]. Many discussions have arisen about how view coordination might be supported. These include discussions on how to link common data between views [6, 7, 22], about how to compare data that is in different views [11], about how to preserve one's mental map from one view to the next [8], etc. However, to date, multiple view research has focused on either introducing specific new methods for revealing relations between views [7, 8, 12, 26, 30], or on creating systems that support a given dataset and its associated tasks [26].

This previous work provides specific between-views methods or techniques to address a specified problem. However, they have not been generalized – designing a good meta-visualization technique is challenging and complex because such a task includes finding solutions for many issues. These include: what tasks should be supported and how between view interference could be handled, etc. Moreover despite the growing need for such techniques no guidelines provide a clear summary of what these important dimensions are. There are many open questions about how to support a visualization researcher or designer during the early stages of creating their meta-visualizations. This problem motivated us to take a different approach. We look at the problem of relations between views from a broader perspective. We investigate the possible range of relations between views, the different types of view-relations; and how they can best be represented. To have a better understanding of this design space we conducted a qualitative study where we asked ten visualization experts to review existing meta-visualization solutions and to generate new ones. They produced more than 70 reviews containing multiple design critiques, and more than 70 sketches containing multiple design alternatives. We carefully analyzed the combined verbal, gestural, and sketched processes during their review and sketching activity. From this analysis, we report a:

1) better understanding of the range and variation in view relations, and
2) range of possible representations of view relations.

Based on a combination of this analysis and the related work we derive a framework that describes the different dimensions of between-view relations. This framework is a tool that can be used as factors to consider when designing a view relation meta-visualization. It provides the different questions and criteria one should take into account during the early design stages of such systems. This framework can also be used to describe the existing view relation techniques. Moreover, the framework reveals an underexplored view relation design space.

1 Clarifying Terminology

Visualization systems create displays of visualizations that are often divided into different spatial regions. When these regions are used to visualize different aspects of a data set, they are often denoted as views. However, the boundary between what is considered a visualization, or multiple views in a visualization, or separate windows is not clear. In addition, the terms view and visualization are often used interchangeably.

In the visualization literature, perhaps the most common use of the term view is to indicate, within a visualization system of a given dataset, a framed variation either in the representation used, or the part of the data displayed [5]. Baldonado et al. defined a view as a set of data plus a specification of how to display that data [2]. Importantly, this definition ignores how views are defined spatially. Collins &

In preparation

Carpendale defined a visualization in VisLink [7] as being a spatial representation of a set of relations on a dataset that is placed on its own interactive plane. Their use of the term visualization notes that the dataset as well as the representation was different. Thus, VisLink is as a system that shows relations between visualizations. Viau & McGuffin argue that parallel coordinates plots (PCP), which are typically described as a visualization technique, could be described as multiple axes, where each axis can be thought of as a 1D "view" of the data [29]. This decision to consider parallel coordinates axes as a view, was suggested because each axis can be used to solve specific visualization goals.

In this paper, our definition draws upon all the above, but does in include boundaries: A *view* is a bounded area that has its own use of spatial organization that displays any variations of datasets and their representations. View boundaries may be represented visually using borders, backgrounds, or similar techniques.

2 Related Work

Many visualization systems show multiple views that display different aspects of a dataset. Multiple coordinated views (MCV) enable exploration of data through a variety of interactions [2]. Brushing and linking is a common coordination technique, in which items selected in one view, are highlighted in other views. Use of color encoding may be shared across the views. Likewise, navigational coordination relates zoom and pan interactions in one view to other views. Most MCVs do not present a persistent visual representation of relations between views, but rely on interactions to let people discover view-relations. Roberts provided an excellent overview of MCVs that discusses exploration processes and meta-information about views [22].

Multiple charts stacked on top of each other that share a common horizontal encoding predate computer visualization [10]. By reusing spatial encoding in multiple charts, they can be considered early ancestors to scatterplot matrices that emerged in the last half of 20th century. Im et al. recently showed a generalization of the scatterplot matrix to display different chart types, matching the data type of visualized variables [14].

DragMag [30] introduced an interactive version of separate magnified windows, often referred to as insets in cartography with place holders in a base window, now commonly referred to as overview plus detail. ConnectedCharts [29] represented relations between data and axes across different views using line connections, similar to PCPs. Unlike PCPs, ConnectedCharts limit the represented relations to those established by interaction. The system reduces clutter by anchoring lines to axes and chart edges.

PCPs were recently extended to offer more flexible spatial arrangements. Lind et al. showed how the axes in PCPs could be spatially rearranged to allow investigation of relations between multiple variables [20]. Inspired by this idea, Claessen and Wijk created a system that allowed flexible re-arrangement of axes, in combination with scatterplots, PCPs, and histogram visualizations [6].

VisLink [7] showed multiple 2D views arranged on planes in a virtual 3D environment. Relations between the views are represented by line connections. By navigating the 3D environment and reconfiguring the position of the 2D views, it was possible to explore relations between different datasets in different 2D representations such as scatterplots and treemaps. Multiple visualizations plus visual line connections let people quickly answer complex questions involving many variables.

Zhao et al. described a hybrid of treemaps and node-link diagrams, combining the space-efficiency with the structural clarity of the two visualization types, respectively [32]. NodeTrix [13] offers a hybrid network visualization system that combines the benefits of node-link diagrams to show global structure and the benefits of adjacency matrices to show local structure. Interaction techniques support reconfiguration of the hybrid visualizations to select between node-link and matrix forms.

Lark [26] provided a meta-visualization of the visualization pipeline to link multiple views. Coordination of views was possible through interacting with views and the pipeline visualization. In Lark, focus was not on relations between views per se, but rather on the relations between individual views and data processing stages, thereby providing a meta-visualization of relations between views.

In GraphTrail [8] new views can be created from existing views by dragging view elements out of a view, and releasing it on a virtual canvas. A representation of the relation between the existing and new view is shown after release. In addition to representing data flow, the technique showed interaction history, which enabled the reconstruction of analysis trails. ExPlates [18] showed a dataflow-based system, that used abstract representations of processing steps between views. GraphTrail and ExPlates both relied on a virtual canvas and pan and zoom techniques, with ExPlates also supporting annotation.

Gleicher et al. surveyed work in information visualization related to comparison [11]. They identified three types of methods of comparing objects: juxtaposition, superposition and explicit encodings. Although their work did not focus on view relations representations, some types of view relations aim to support comparisons.

Javed and Elmqvist reviewed composite visualizations in the literature, and derived a design space expressed in terms of spatial mapping and the relations between data items in views [17]. Their work focused on data relations, but views may have other relations, which may be relevant to some tasks or analysis.

Inspired by the variety of meta-view relations suggested by the literature and a study where a group of analysts discuss the need for meta view representations [19], we conducted a qualitative study to better understand the breadth and scope of this problem. Our study aims to expand our understanding of how between-view relations might be represented and to better understand the issues that arise when creating between-view representations.

3 Study Methodology

We conducted a qualitative study in which we invited people work with, discuss, and sketch representations of view relations. The aim was to expand the palette of possible representations of meta-visualizations and to improve our understanding of these different types of meta-visualizations, paying particular attention to when and where they were of interest. Rather than designing, implementing, and testing one single possible design, we chose to work towards expanding our understanding of the role of meta-visualizations in visualization and interaction design, by considering many meta-view visualization alternatives. To do this, we developed many alternative designs, and implemented them as low fidelity prototypes. The prototypes allowed us to present several ideas to participants and run a review of these designs. We were interested in the participants' interpretation of the relations represented in the designs. This allowed us to gain knowledge of the strengths and weaknesses of the view relations and their representations.

3.1 Participants

For participants we selected people who were currently actively working with designing, implementing and evaluating visualizations and visual interfaces. Our participants had all published in top venues in visualization, interaction design, or human computer interaction. They were all current active researchers. There were six men and four women, most had a related MSc, and one had a related PhD. All were familiar with large displays and with using pen and touch interaction.

3.2 Study Approach

We asked participants who were currently deeply committed to the world of visualization and interaction design, to review our proposed designs and to suggest alternatives. In this way, the study methodology resembles an expert review. We did not ask the participants to review a single system, but rather to both review and extend different possible design ideas for representing between-view relations. We argue that our choice of methodology offers a sweet spot between an expert review [28] and semi-structured interviews with people who might use these types of systems. In contrast to other evaluations of

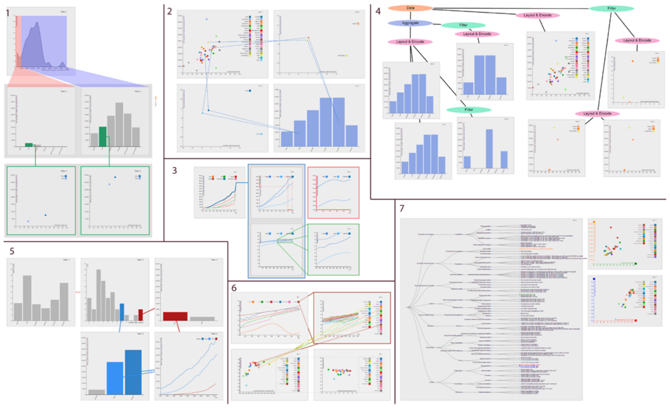

Fig. 1. Overview of design scenes. Full resolution images are available from supplemental material and interactive versions from http://website.

single representations of view relations [8, 15, 26], our approach opened several different opportunities such as understanding what designer would like to see rather than discovering if a particular approach was to their liking. Thus, the study took the form of a semi-structured inquiry–based interview on alternative design suggestions. Additionally, since it has been shown that participants provide more feedback when presented with several alternatives [27], we also offer several alternatives. Our study design method allowed us to explore the advantages and disadvantages of different relation types and methods of representation. In doing so, we are able to obtain a broader understanding of view relations, and draw inspiration by the variability apparent through the many designs created by our participants. The study attempts to understand how meta-visualizations may help people understand and navigate many views, and puts less emphasis on visualizations of the data. This study does not focus on the domain of the visualized data or the related data tasks, but more on abstract visualization tasks. Thus, based on Munzners' nested model for visualization design and validation [21], we argue that using visualization experts as study participants is sensible.

3.3 Apparatus

During the study, participants worked with seven scene designs. The scenes consisted of visualization views and between-view relation representations. Some scenes captured ideas from related work, while others were novel. Scene 1 and 5 are inspired by GraphTrail [8] (Fig 1: 1, 5), scene 2 by VisLink [7] (Fig 1: 2), scene 3 by DragMag [30] (Fig 1: 3), and scene 4 by Lark [26] (Fig 1: 4). In addition, scene 6 was based on the idea of considering legends in relation representations (Fig 1: 6), and scene 7 on the idea of showing meta-data in separate views (Fig 1: 7). These scenes are not intended as faithful reproductions, but instead are used as conversation catalysts. The goal of offering many alternatives was to allow participants to compare ideas and to provide variability to the study [27], inspiring participants to come up with their own ideas. The scenes were implemented in D3 [3] and ran in a browser (Chrome version 31). Figure 1 shows screenshots of the scenes. All scenes visualize data obtained from OECD (http://stats.oecd.org). The scenes were shown on an 84 inch, 4k display at 30Hz supporting touch and pen interaction. We conducted the study with a large display, to provide participants the space of a large display area to be able to layout view arrangements and use space to think [1].

3.4 Procedure

Each session lasted approximately 1½-hours, and consisted of three phases. In the introductory phase, participants were briefed about the study; signed a consent form; and answered a short questionnaire about demographics and experience with data analysis, visualizations and the data and technologies used in the study. We then introduced the OECD dataset used in the design scenes.

The main phase of the session consisted of two parts. In part A, participants looked at and interacted with the seven scenes that each visualized some aspect of the OECD data and included some meta-visualizations. In part B, participants sketched their own relations representations between scene views based on a description of the views. They sketched on top of the same design scenes stripped from showing view relations. Participants used a digital pen to sketch. To account for bias from exposing participants to our representations before sketching their own, half of the sessions were conducted in AB order

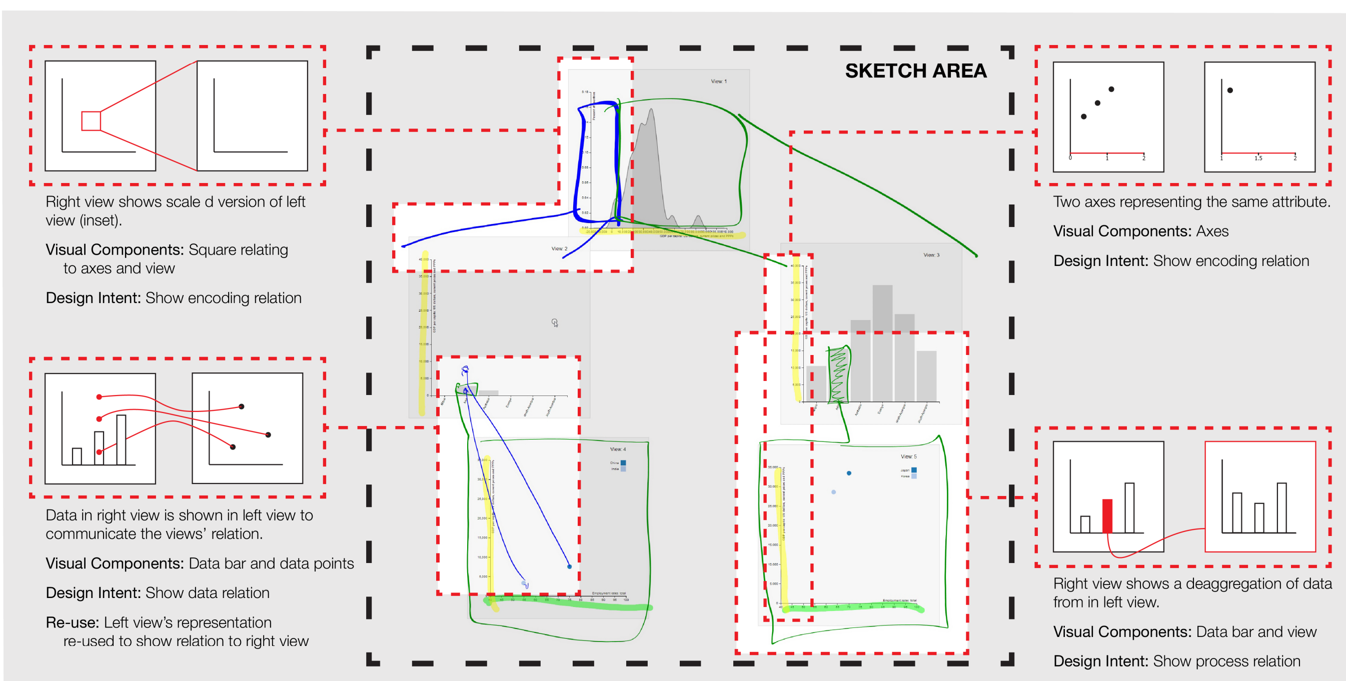

Fig. 2. Process of analyzing screenshots from experiments. The sketch area (center) shows a sketch by participant 5 in scene 1 (see fig. 1). We analyzed the 70 sketches by identifying between-view relation concepts which we present in the study results section.

(i.e., first part A, then part B), and the other half in BA order. Similarly, the order of scenes was randomized to not favor specific scenes, although within sessions, part A and B used the same order.

During part A, we probed participants with questions about what they saw. We asked factual questions, descriptive questions, and evaluative questions. for instance, we asked participants to tell us the GDP in 2010 for Canada, to describe the relations between two views, and to state their preferences for the relations shown. After experiencing and discussing a scene, participants were invited to ask questions about the representations, enabling us to improve our knowledge of their interpretation. We continued to the next scene, when participants had answered our questions, and we theirs.

During part B, we probed participants with questions similar to those in part A. This time relating to what they sketched. We asked participants to describe their sketches and choices of representations.

In the concluding phase, we debriefed participants in a short semi-structured interview. During this interview, we asked participants; (a) which benefits and disadvantages they observed from seeing the relations represented visually; (b) which relations seemed most important and why; and (c) which methods of representing relations seemed most useful and why. Finally, we asked participants about the study methodology. We asked how they thought the tools they used during the session had influenced their ideas and sketches (e.g., if they felt limited by the detail they were able to sketch or choice of pen color).

3.5 Data collection

We recorded the experiment using a video camera pointing towards the display from an approximate 30-degree angle at approximately 4 meters distance, zoomed to show the 84" display centered in the image. An audio recorder was setup close to the display to make sure that we obtained a good and intelligible audio signal. Additionally, we used software to grab the display state during the experiment.

3.6 Analysis

We analyzed the recorded material based on a grounded theory approach [16, 25]. Although we started the study with some ideas of what to look for (based on related literature [6, 7, 29, 30, 32, 8, 11, 13, 18, 17, 22, 23, 26]), we also looked for new ideas and concepts while analyzing the gathered data.

In the first analysis pass, the first author went through all the material, keeping notes of interesting moments while obtaining an overview of the material. During this pass, findings were discussed with the second author in meetings held for approximately every 60 minutes of observed video. Concluding this pass, we identified major themes that we wanted to develop. In the second pass, notes taken during the first pass were used to revisit the video source material in context of the major themes. During this pass, we used screen captures of the final state of views and sketches for each of the 7 scenes in part A and B. We base the following section primarily on our analysis of the identified themes, as well as findings from these images (see figure 2).

4 Study Results

In this section, we describe our observations of participants' behavior. Participants told us about their design ideas, both criticisms and suggestions, either verbally, or via gestures, or with sketches and annotations. In analyzing the observations, we gave equal weight to all the different ways in which they indicated their ideas. We read the transcripts, we watched the videos, and we looked at the visuals on the screen captures. As concepts for codes emerged, they often would include a range of possible participant indications. Also in converse, a particular design for showing meta-view relations would often make use several of the concepts for which we coded. Table 1 provides an overview of the countable results according to our coding concepts. The rows in Table 1 are the concepts, the columns, S1 to S7, are the scenes. Column D stands for concepts that emerged during the debriefing and column T is the total number of participants who used this concept. Note that T does not add the numbers in the row because it is possible that one participant used a particular concept in many scenes.

4.1 Illustrating our coding concepts

Here we provide a brief definition of each of our coding concepts and illustrate them with both common and more unusual examples.

Task: covers all situations where participants considered the tasks that representations of between-view relations might support.

Examples include a participant stating that the importance of seeing particular types of relations is dependent on tasks and goals: *"It depends on what you want. If you want to follow a specific country, then this relation, in that case is more important. It completely depends on the context"*.

Interaction: covers all situations where participants considered interaction as part of seeing, understanding or showing relations.

Examples include considering how interaction could help to set up relations, for example by dragging colors from a palette over the attribute tree in scene 7. The participants often moved views by rotating (figure 3, right) or aligning views spatially would show their relation.

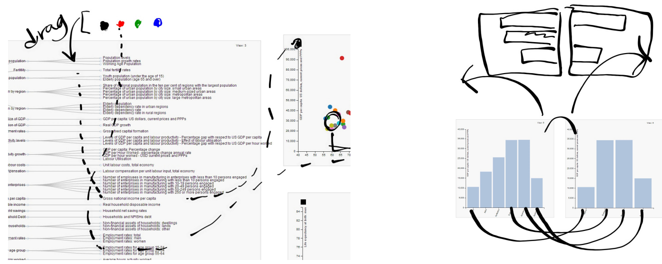

Fig. 3. Participants considered different methods of interacting with views to configure and show relations and their representations.

Brushing & Linking: covers participants' sketches of or considerations for the use of brushing and linking to show relations between views. As expected, brushing and linking were well known to participants and were often referred to in passing as possibilities to be used in addition to other types of between relation representations.

Examples include brushing the histogram in scene 1 to highlight parts of data bars in another view (see Figure 4) or suggesting only to use color for temporary encodings (i.e., brushing and linking).

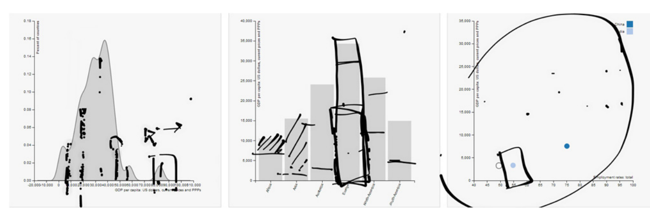

Fig. 4. A participant sketched a compact design for scene 1 in detail. The design involved brushing and linking between views at the same hierarchy level.

Concepts	Scenes								
	1	2	3	4	5	6	7	D	T
Task	1	0	0	1	1	1	0	1	2
Interaction	2	2	1	3	1	1	4	3	6
Brushing & Linking	1	2	0	2	1	1	1	0	3
Axis Relations	3	1	3	2	2	5	0	1	5
Legend Relations	0	3	0	0	0	6	1	1	7
Grouping Views	4	3	2	4	2	1	0	1	8
Visual Components	8	6	7	6	7	7	4	0	9
Re-use of within-view Representation	4	4	0	0	2	2	1	0	7
Direction, Flow & Order	4	1	1	0	0	1	0	0	5
Line Arrows	5	3	3	2	4	5	2	0	7
Strength	1	2	0	1	1	0	1	0	4
Clutter & Scalability	1	3	0	1	0	1	2	4	4
Interference with Views	5	1	2	0	1	0	1	1	6

Table 1. Overview of results showing the number of participants considering a code. Second last column, D, shows debriefing. Last

Axis Relations: covers all methods of showing that two or more axes or parts of axes relate. Axis relations included axes that encoded the same attribute, axes that encoded the same or an overlapping value range of an attribute, or simply axes that encoded related attributes.
Examples include participants sketching relations between axes by highlighting axes (see figure 2) to help obtaining an overview of what the different views showed; or connecting axes' ranges by lines. A participant commented that different aspect ratios between two views made it difficult to see that one showed a zoomed view of the other.

A participant considered that sometimes views that look alike or dissimilar, which is difficult to spot without some kind of support: *"The fact that you have three visualizations that all look very similar, while one of them have different axis labels. I feel like that should be highlighted in some way, right. Cause otherwise you're playing this game of spot the differences. And I don't think [people] are very good at that"*. The participant later noted for scene 7's relation representation *"at a glance you know that none of the axes are the same"*.

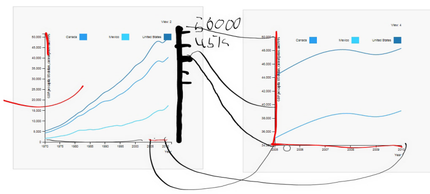

Fig. 5. A participant sketched axis range relations between two views in scene 3.

Legend Relations: covers all methods of showing legends or parts of legends that relate, and included identical legends, legends that used the same spatial layout for data, and legends that partly represented the same meta-data.

Examples include connecting rectangles sketched around similar legends in two views and extracting legends from views and connecting one legend to all the views. A participant stated, *"it is nice that the spatial position of legend items [match across views]"*.
Grouping Views: covers different methods that participants suggested for grouping views.

Examples include favoring the possibility of seeing more data in one view, integrating two or more views into one. or encircling multiple views to show that they were similar such as showing the same data, or using the same encoding. A participant suggested to *"connect views that show the same data with curvy or dotted lines"*. We also observed the shaded area in scene 1 that was used to group views, tended to confuse participants until provided an explanation.
Visual Components: covers all situations where participants considered which components of a view to use in representing relations.

Examples include situations where participants explained their reason to use particular components *("I want to connect this to the legend to reduce clutter" or "I connect to the legend to not interfere with the lines"*, see Figure 6).

Participants used all the different visual components of the view, the data and the meta-data. For instance, they connected data points and bars to other views' borders and sketched rectangles to group parts of data in one view to data in other views. A participant considered how to show an overview plus detail relation between two line plots, and suggested to connect the line start and end points in the detail view.

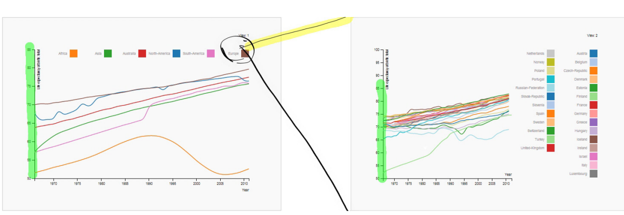

Fig. 6. A participant sketched a relation representation between a legend and a view in scene 6.

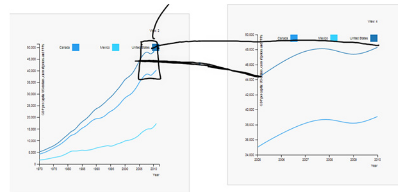

Fig. 7. A participant connected line start and end points in a detail view with the same points in an overview in scene 3.

Re-use of Within-View Representations: covers visual designs where participants used parts of the views' representations to show relations between views.

Examples include re-using the color of linked data points for the color of the link; connecting data points in one view to data bars in another view; using line end points to encode the specific data values on the vertical axis in both views (see figure 2 and 8); and merging lines from multiple legend items and connecting these to data bars in other views, allowing line thickness to represent the fraction of the data bar indicated (see figure 7) to *"encode more information"*.

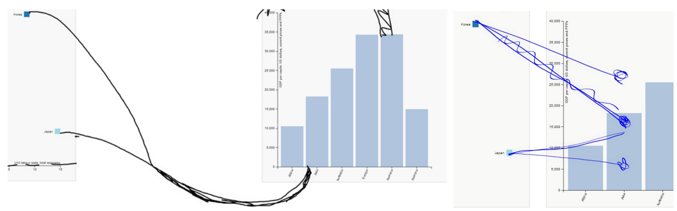

Fig. 8. Two examples of participants' re-use of within-view representations in scene 2.

Direction, Flow & Order: covers situations where participants considered conveying view relations' direction, the flow of data between views, or the reading order of views.

Examples include participants saying that some marks *"make you read the visualization in a specific order"*; while arranging views, stating *"I am reading it left to right, top to bottom"*; or stating *"so this takes that data over there [pointing with both hands]"*, and showing with hand gestures how views connected, suggesting that the visualization was *"trying to tell a story"*.

Line Arrows: covers participants' use of arrows in sketching. All participants drew arrows similarly except for one, who drew arrows in the opposite direction.

Examples include arrows between data bars and legends, which were suggested to show less direct connections between data in the two views (see figure 9); and arrows between country legend items grouped according to their continent and views that show this continent (see figure 9).

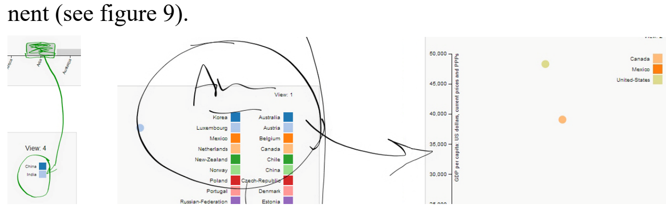

Fig. 9. Two examples of participants' use of line arrows. Left, line arrows connect from a data bar to a legend. Right, line arrows connect a legend item group to a view.

Strength: covers situations where participants talked about relations or connections in terms that relate to strength or when they sketched relation representations that conveyed strength. When considering weak relations, the participants mainly described the relations as "weak" or "not strong", whereas they mainly used "important" when considering strong relations.

Examples include stating *"This connection is not strong"* regarding a relation between two bar charts in scene 5 that showed the same data with different aggregations; using curvy lines to signify weaker relations than straight lines.

Clutter & Scalability: covers situations where participants considered the problems that showing many between-views relations can cause, by hiding or cluttering the data shown within views.

Examples include connecting lines from data bars in a bar chart to legends in a scatter plot instead of connecting to data points, to reduce clutter; using transparency for links between data bars and data points; and expressing concerns for using the same color across many views.

Interference with Views: covers any added visual indications of view relations that decrease peoples' ability to focus on or understand data shown within views. In contrast to Clutter & Scalability that consider the amount of shown relations, this concept highlights that few poorly designed between-view representations can negatively affect comprehension.

Examples include concerns that highlighting a views' border and axes to indicate an overview plus detail relation between two views took focus from the data in the detail view; and concerns about between-view lines connected to within-view lines.

5 From Concepts to Dimensions

In the results section, we described detailed observations from studying participants' considerations about view relations as concepts, which we based on open coding from our analysis. These concepts worked well to convey the range of thoughts and ideas that participants expressed. However, to make them useful, we needed to examine these concepts from the perspective of providing practical advice about designing concrete meta-view relation representations. To evaluate existing use of meta-view relations and to offer generative advice about creating new ones, we needed concrete, practical suggestions of what to consider. Therefore, using these concepts as a basis, combined with drawing from the literature, we assembled a framework that is composed of six different dimensions of view relations.

We provide an overview of the mapping between concepts and dimensions in Figure 10. The concepts we used for coding are on the left hand side. The framework dimensions; design intent, visual components, re-use of view representations, direction, strength, and interference with views are on the right hand side. Note that two of the framework dimensions, design intent and visual components, have sub-components. The colors are used to reinforce the framework groupings and the edges in the bi-partite mapping are colored according to their destination framework dimension. Some coding concepts like strength map directly to a framework dimension. Others, like visual components, map to visual components in the framework but required dividing for practicality. This is because the concept visual components concerns both the general idea of choosing the components that are used as part of showing relations, as well as the individual possibilities. Likewise, the concept "axis relations" concerns showing encoding relations, as well as using meta-components as part of showing relations. This does not exclude the idea of showing such relations with another visualization technique

Whereas many coding concepts described the visual properties that could be used in the meta-representations that participants considered, the dimensions consider properties of the *views' relations* in themselves, which might be shown with different visual properties or techniques. The dimensions of view relations are loosely orthogonal. This means that it is possible to design for one dimension at a time, although it may be more effective to consider the dimensions together. Next, we present the framework.

6 The Dimensions of View Relations Framework

The many techniques to show view relations as presented in related research, inspired us in designing this study. Many similar as well as many novel view relations techniques are present in our study results. We take our results, combine them with related work, and introduce a framework, *Dimensions of View Relations*. In describing our results,

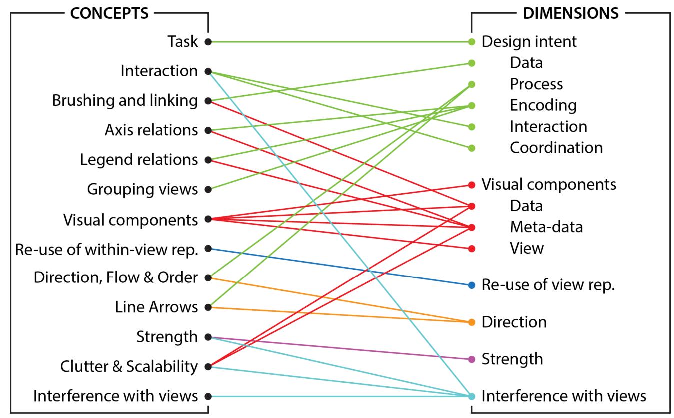

Fig. 10. Mapping the results' concepts to dimensions of view relations.

we focused on participants statements. In contrast, the framework considers view relations in terms of possibilities. Additionally, the framework draws upon a broader foundation, also pulling from other research.

The framework offers six dimensions of view relations and their representations: design intent, visual components, re-use of view representations, direction, strength, and interference with views. Next we describe these six dimensions and their components, followed by an explanation of making use of the framework.

1. ***Design intent*** considers what the purpose is of showing a relation representation, from a designers' perspective. Thus, a design may be useful for other purposes than what the focus of the design was, and a single design may cover more than a single *design intent*. We used the word intent because intent captures a designs' idea, rather than what it enables. Intent can be multi-faceted: a relation representation that shows data relations may also show process. For example, if a view shows a subset of data points from another view and the data points are connected, then the relation shows both data *and* process. In the following, we describe five *design intents* of showing relations:

a. ***Data*** relations intend to show the relation between data present in two views, conveying which data is affected using different visualization techniques, choices of encoding, or data processing. Examples of showing data relations include using color similarly in two views (see S2 to S7) and linking data points across views (S2, [7, 23, 29]). Participants considered data relations in all scenes.
b. ***Process*** relations intend to show how data has been processed or transformed between two views, e.g., through filtering, aggregating, deriving, or any other process. Lark [26] and ExPlates [18] showed processing explicitly with lines connected to views. GraphTrail also used line connections [8], but was not explicit about how data had been processed between views. VisTrails [4] conveyed process implicitly through views' spatial position.
c. ***Encoding*** relations intend to show the data encoding differences or similarities between two views, e.g., by using highlighting or connecting axes, or connecting legends. In Lark [26], views' encoding relations were shown explicitly through the InfoVis pipeline representation.
d. ***Interaction*** relations intend to show how views relate based on people's interaction with views, e.g., by having used one view to create another or by whom created or positioned a view. GraphTrail [8] and ExPlates [18] (to some degree also ConnectedCharts [29]) used interaction relations to show analysis history, while the intention with Lark [26] was to support collaboration by showing interaction relations.
e. ***Coordination*** relations intend to show how views are coordinated, e.g., by brushing and linking techniques. We are not aware of any related work that shows coordination relations explicitly. A participant in our study suggested these relations might be experi-

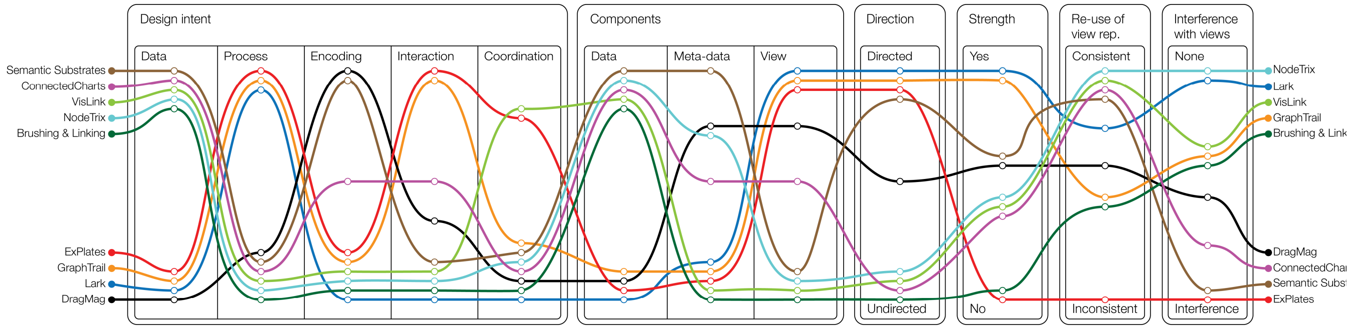

Fig 11. Overview of framework dimensions used to describe related work in terms of the framework. For design intent and components, top means that the work considers the dimension. When work is not positioned top or bottom in a dimension, the dimension is only partly considered. For example, DragMag is primarily designed to show the connection between detail views and the overview, and partly designed to show where the detail view has been positioned in the overview. Meta-data and views are used in DragMag. Direction (why). Strength (why). Re-use (why). The connections between views interfere somewhat with the overview.

enced through interaction (e.g., brushing). We suggest that showing coordination relations explicitly may be useful in contexts where many people use many views.

2. *Visual components* delineate the different components that can be involved in showing view relations. These may be ordered in a three-level hierarchy:

a. ***Data components*** comprise visual marks that represent data: points in scatterplots, bars in bar charts or rectangles in treemaps. VisLink [7] shows relations between data components.

b. ***Meta-data components*** comprise factors included in the visualization to help with readability such as axes, legends, and grid lines. For example, Semantic Substrates [23] showed relations from a squared area (meta-data components) to data points (data components).

c. ***View components*** comprise factors that contain and separate the view from the rest of the display such as view borders, corners, background, and title. GraphTrail [8] used line connections between views' borders (view components). The color of the line mapped the selected data in views (data components).

Because all relations are between two views, different component levels might be involved in the two views.

3. *Re-use of view representations* captures how data encodings used within views may be used in relation representations. For example, a line connection between two views can use the views' internal color encoding to color the lines. Similarly, a bar in a bar chart may be divided into a stacked bar, thereby using the spatial layout of the bar chart to make it easier to understand a relation to another view.

We denote relation representations that re-use views' representations as *consistent* with the view representations. Lines colored similar to the data points they connect are consistent relation representations. Likewise, we denote relation representations that use the views' representations to convey separate information as *inconsistent*. Lines representing view to view relations that are colored similar to data points in the views are inconsistent.

While we are not aware of work that focuses on *re-use of view representations*, the idea is used in some systems. For example, VisLink and Elzen & Wijk [7, 9] used colors within views to color lines between views, while ConnectedCharts [29] used the position of data points to anchor relation lines to axes and chart edges. In contrast, this was frequently discussed by our participants (7/10).

4. ***Direction*** of relations captures that view relations can be can be directed or undirected. If source and destination views exist, the meta-view representation may show this. For example, an arrowed line may connect a source view to a destination view [31], views' position may show direction (e.g., using reading order) [4], a line may connect the right side of a source view to the left side of a destination view [18], or views' component hierarchies may show direction (e.g., a line between a data bar and a view show direction implicitly from the data bar to the view). This also implies that representations of directionless relations might focus on showing relations between components at the same level of the component hierarchy (i.e., data to data, meta-data to meta-data, or view to view).

5. ***Strength*** of relations captures that view relations can vary from weak to strong and the relation representation can reflect this, similarly to the notion of edge weight in graph data. *Strength* may comprise both negative and positive values, thus implying that representations may show that two views are related *or* unrelated, for example to show that two views that look similar are actually different. Any relations between views can influence how to show strength, such as interactions with the system (e.g., brushing, proximity data, and user profile) and the visualized data (e.g., amount of common data points). Additionally, combinations of relations can be part of numerical computations of strength, which visual representations can show directly or alternatively, influence when to show a relation. Most systems show strength implicitly by showing a subset of possible relations, based on an assumption of a static importance metric. For example, hovering over data points to highlight related data points (i.e., brushing and linking) uses binary interaction data (hover/not hover) to show binary relation strength (highlight/don't highlight).

Elzen & Wijk [9] and Henry et al. [13] used aggregate links in which size encoded number of links between views (in what is described as an overview) and adjacency matrices, respectively.

6. *Interference with views* captures that view relation representations may interfere with within view representations. It is thus important to consider this in designs of relation representations. For example, to reduce interference, line connections between data points in two views, may consider the spatial layout within views by routing lines around other data points. Similarly, aggregating lines, connecting to labels rather than data points, or aligning lines to axes or borders, can reduce interference. Additionally, color used to show relations might interfere with within-view representations, if using conflicting or strong color encoding possibly, taking focus from the view itself.

Steinberger et al. [24] routed lines along view borders to reduce occlusion of salient regions. Similarly, Viau & McGuffin [29] fixed lines connecting data points to axes and view borders to reduce clutter.

7 The Framework in Action

In this section, we will show how the framework may be used, both to describe existing research prototypes and to generate new relation representation designs.

The dimensions in this framework may be combined to describe existing relation representations and to generate new ones. For instance, in the literature there are many examples that show combinations of these dimensions. Note, that although the dimensions describe important aspects of view relations representations, they do not describe all relevant aspects. For example, the dimensions do not describe the style of the representations.

To show the descriptive power of the framework, we will traverse it by walking through how Semantic Substrates [23] fits in the framework as shown in figure 11. By walking through it, we will demonstrate how it is possible to use the framework to consider each dimension of how relations are shown between views.

In the framework diagram (Figure 11), Semantic Substrates [23] is at the top of the left hand list of related research. Following its brown line from left to right, we see that the design intent of Semantic Substrates is data and encoding. Semantic Substrates shows data relations since they link data item to data item. Further, they make use of encoding when they reduce links between the views to specific regions of the views. Next, under visual components, we see that Semantic Substrates shows both data and meta-data relations. Shneiderman et al., [23] state that they aimed to show directionality in their links for which they use arrows. This is also shown in the framework diagram. The brown line for Semantic Substrates is drawn through the middle of the strength box in the framework diagram, because links are shown based interactions rather than assigned some system based weight. The way Semantic Substrates uses color for the links is a subtle example of re-using within-view representations in between-views relation representations, which is why it is marked above the middle in the framework diagram. Finally, node-link diagrams often results in clutter, and this can with lots of links in happen in Semantic Substrates as well. Although, the way their interaction helps to handle clutter made us position it towards the middle of the framework diagram.

8 Discussion

Here we discuss the framework dimensions and their implications. Since our participants were mostly designers (either interaction designers, or visualization designers) when we asked them to think about the between-view relations, they discussed and acted upon this by considering possible designs. This section reflects much of their discussions as they talked about what they would consider important in designing between-view relation representations.

8.1 Design intent

Many participants considered the role that task and context has in showing view relations. Participants underlined that an optimal solution for a given problem depends on the task. Thus, in designing relation representations, just as any other visualization, it is often a matter of understanding which tasks to support, and then designing for that task. We describe the potential task our participants considered, and describe how they suggested showing relations that might support a task.

Participants almost never considered using relation representations to understand data in itself. The large majority of participants that considered how to understand data, considered this by combining data from multiple views into one view, thus disregarding the idea of keeping data in multiple views. This contrasts other work that has aimed to use relation representations to help people understand multidimensional data (e.g. [7, 29]) using e.g., coordinated views. Since the literature has many examples of successful between view relation representations that focus on relationships between data in separate views, we still consider this an important part of the framework.

Nine participants considered process relations, through sketching arrows, gesturing direction, or talking about data flow. Representing such relations was important to participants, and they considered varied possibilities for showing these. In contrast to how Lark [26] showed indirect relations between views by incorporating the InfoVis pipeline, most participants considered showing data process relations directly between views or their visual components, and stated they preferred such direct representations.

Participants considered many variations of relations between meta-data components. According to participants, they sometimes considered these due to the connected data or the data relation. Particularly, participants suggested many designs that involved axes and legends. These designs helped reveal how different views showed data in similar or different ways. For example, the designs in scene 3 and 7, focused on scale and hierarchy in axis relations. When participants worked with these scenes' axis relations, they primarily considered how to support navigation and how to understand the views' similarity. While participants considered supporting these goals by showing relations between meta-level components directly, they also considered encircling groups of views for a similar effect.

Participants considered interaction in mainly two aspects. First, participants considered interaction in the way of e.g., brushing and linking. Second, participants considered views related through interaction. For example, they considered that relation representations can tell a story about data or show that data in one view is based on data in another view. Few participants however, considered showing these relations (e.g., as in GraphTrail [8]).

Participants rarely considered coordination relation representations. In fact, when asked, participants found these relations to be unimportant and suggested these relations may simply be experienced through interacting with a system. We are doubtful whether this scales to showing more than a handful of views, but suggest that more research is needed to understand this.

Our results suggest that many of the tasks that relation representations may support, are meta-level tasks (e.g., obtaining and keeping overview of views). For example, although participants considered relations that could help understand data, they focused on relations between views that might help meta-analysis tasks such as navigation.

8.2 Visual components

The participants considered a large variety of visual components to show relations: Points, bars, lines, axes, axis legends, axis labels, legends, legend items, view frames, and groups of views. While sketching, participants carefully considered how to show relations and which visual components to use. From these, we have identified three groups of visual components: data components (e.g., data points, bars, and lines); meta-data components (e.g., axes, axis legends, axis labels, legends, and legend items); and view components (e.g., view borders, corners, background, and title).

An example of the usefulness of distinguishing between visual components arose in scene 5, where participants raised concerns about a relation representation that used both data and view components. The scene used a colored line connected from a data bar in one view, to the border of another view, but the color of the line matched colors of data in both views, thus posing a problem; where the line connection indicated a data-to-view relation, the color indicated a data-to-data relation, thus making the relation unclear. We suggest this problem arose because the design used different components to show the same relation. On the other hand, a participant sketched a design for scene 1 involving data components in two views and view components in one of these, which worked well to convey the relation (see figure 2, bottom-left). We find these contradictory results interesting, and suggest that more research is needed to understand when to use and when to avoid using multiple component levels in showing relations.

Participants suggested that views with similar legends might share one legend arranged in a separate rectangle from the views (i.e. using its own spatial arrangement, cf., section 2). This raises the question of whether it is useful to make a clear distinction between a view and relation representation. Similarly, from participants' considerations, we question whether to understand view 1 in scene 7 as a view or a meta-data visualization.

What is considered a data component in one view might be considered a meta-data component in another, thus questioning the concept of visual components. For example, two views may show the same attribute differently. In one view, aggregate data bars may show several attributes. In another view, an axis may show one of these attributes. The result is that the visual representation of the attribute is considered data in one view, and meta-data in another. In this light, some notions may make sense with-in views, and some notions between views.

Participants knowingly suggested contradictory uses of visual components in a scene or in different scenes. This may be an indication that relations may be shown in different ways, depending on the visualized data, the context or task or other factors.

8.3 Re-use of views' representations

The participants considered alternative techniques of showing relations by re-using within-view representations between views. In several occasions, the techniques worked well to convey additional information not present in the views. In other cases, re-using within-view representations worked less well, and may even confuse people. These ideas point to a broad range of possible visualization techniques, which currently seem underexplored.

8.4 Direction

Nine out of ten participants considered relations that showed direction. Often, participants sketched arrows with a great variety of visual styles. It appeared that the idea of showing direction was more important than the style. While arrows may not always be necessary, the number of arrows in the sketches is remarkable, considering their rare use in related work.

Participants also considered inferring direction from views' spatial arrangement (e.g., reading-order). This provides an argument for allowing people to use spatial arrangement to annotate views' direction relations in an implicit manner and repeats suggestions in earlier work (e.g., [8]).

Although some participants almost exclusively sketched lines with arrows, all participants considered relations that had no implicit or explicit direction. In addition, some participants sketched two-way arrows, which seemed to indicate bi-directionality direction.

8.5 Strength

Few participants considered relations' strength. We mainly observed this from what participants said, for example, that one relation was stronger than another was. Strength was primarily observed in relation to interaction, where showing a relation could depend on the strength itself, as well as other factors (e.g., brushing, proximity data). Some participants used the notion of importance, to the same effect.

Participants primarily talked about strength when considering whether to show a relation. Thus, while understanding strength as a continuous scale, the choice of whether to represent a relation seemed to be binary. Strength thus relates to visualizations based on degree of interest. A participant also talked about showing that views are different, thus implying a type of weighting.

8.6 Interference with views

Many participants considered between-view relation representations' interference with views. Some designs ignored the contents of views, except for the connection to other views. Other designs thoughtfully considered the contents of views, in relation representations.

In some situations, participants considered showing relations to meta-data components instead of data components. Participants sometimes considered this to reduce clutter or possibilities for misleading visualizations, such as when connecting a relation line to a line.

Many participants expressed concern that lines might interfere with data. Surprisingly, no participants suggested line shapes more complex than curvy lines. In contrast, they offered many suggestions for representing relations less indirectly to legend items or axes. Designs such as presented in Viau et al. [29], which anchored connections between views to axes or borders, were not considered. We expect that the tools such as pen, touch, and scale of sketches that were available to participants made such designs impossible, which methodological inquiries during debriefing supports (e.g., *"[I] could explain ideas when tools were inadequate"*, *"real whiteboard would have made it easier to draw"*). Many participants considered clutter as the largest drawback of relation representations, both during sessions and when asked specifically about drawbacks during debriefing.

9 Limitations

9.1 Scene designs

The choice of scene designs that participants saw possibly introduced bias. Sources of bias include the choice of: 1) visualized data (OECD data), 2) visualization methods (scatterplots, bar charts, line charts, dendrogram), and 3) which and how relations were represented. Considering the visualization methods, participant 1 said: "Given these representations, I will only think based on the representations I have available". Unsurprisingly, this means that a group of our findings relate closely to the visualizations used in the design scenes. However, there are many findings that can be applied more generally: The specific visualization types had little impact when participants considered how to show relations between data points in two views or to show views that make use of similar encodings. Consequently, we argue that the presented framework to a large extent is disconnected from the actual visualization methods, and does contain generalizable findings that may readily be used for other visualization methods.

9.2 Scene order

It is possible that seeing suggestions of view relations first influenced participants. For example, participants who started by sketching (part B), used less time for sketching and their sketches were less detailed than the participants who started by viewing our relation designs (part A). This is shown in the average times participants spent. Participants in sequence AB spent 85 minutes in total (A: 53m, B: 32m), while participants in sequence BA spent only an average of 70 minutes (B: 41m, A: 29m). In addition, analyzing screenshots of the final sketches of each design scene showed that BA participants had used less ink and had less detailed sketches than AB participants.

Participants in AB session order were influenced from seeing our relation design suggestions. This is supported both from the sketches that participants drew, as well as participants' verbal statements. The bias suggests that reversing session order for 5 participants was a sensible methodological choice. On the other hand, sketches also show that participants that saw our relations before sketching, sketched more than participants who sketched their own ideas before seeing our relations. In addition, participants' statements showed awareness of this bias. For example, a participant said: "One thing I want to make clear is that, a lot of times I'm thinking, oh I saw that before, therefore I shouldn't do that anymore. And I'm like trying to rethink how to do it". In reverse, another participant said: "I was biased because I kind of remembered what you did, and some of them I liked, and some of them, I did not like, but I couldn't think of different representations". This suggests participants were biased both to sketch designs similar to, and different from, designs they had seen before. Many of our observations occurred across the two conditions.

Another possible limitation is that the study set up was only partially interactive. The participants could sketch freely, and could move views around. However, they could not make new views. Thus thinking about showing interaction relations may not have been a priority.

10 Conclusion and future directions

Through noticing the growing prevalence of research on between view relationships and combined with discussion with data analysts who pointed out how important multiple views were with complex data, we identified the importance of directly studying to best represent between view visualizations. Considering the importance of being able to track complex, multi-person, multi-view analysis processes, we consider that our study on between view meta-visualizations is just a beginning of this research direction. However, our observational study generated a considerable amount of rich data from which we have derived a *view relations* framework, which offers six dimensions of view relations and their representations:

- design intent,
- visual components,
- re-use of view representations,
- direction,
- strength, and
- interference with views.

We illustrated this framework with examples from our study and showed how this framework can be used to describe existing literature. Figure xx, shows the framework dimensions and plots existing example from the literature. In this diagram one can also see many possible paths that are not yet explored and may lead to new possible between-view relation representations. Also the framework dimensions can be used as a practical guide, offering six topic that should be considered when designing between-view relation representation.

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