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Exploring Data in Virtual Reality: Comparisons with 2D Data Visualizations

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Abstract
Virtual Reality (VR) has often been discussed as a promising medium for immersive data visualization and exploration. However, few studies have evaluated users' open-ended exploration of multi-dimensional datasets using VR and compared the results with that of traditional (2D) visualizations. Using a workload- and insight-based evaluation methodology, we conducted a user study to perform such a comparison. We find that there is no overall task-workload difference between traditional visualizations and visualizations in VR, but there are differences in the accuracy and depth of insights that users gain. Our results also suggest that users feel more satisfied and successful when using VR data exploration tools, thus demonstrating the potential of VR as an engaging medium for visual data analytics.

Author Keywords
Virtual Reality, Data Visualization, Data Dashboards

ACM Classification Keywords
H.5.m [Information interfaces and presentation (e.g., HCI)]: Miscellaneous.

Introduction
Data visualization paradigms are often employed as a starting point for data exploration. Visualizations

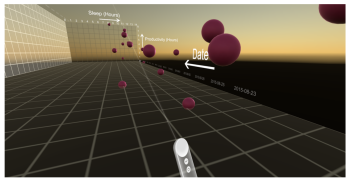

Figure 1: Be The Data (VR)

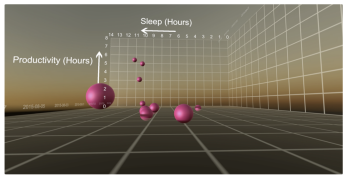

Figure 2: Users can navigate around the VR environment, moving (using the controller) and looking (by adjusting head angle) in all three dimensions, immersing themselves in the dataset

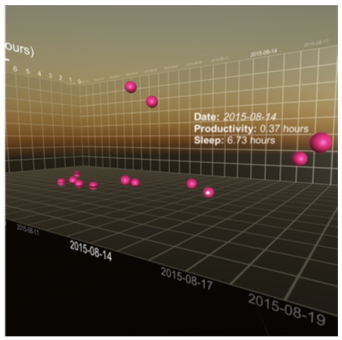

Figure 3: Pointing the Daydream controller and 'hovering' over a data point displays its' values in all three data dimensions (Date, Productivity, Sleep)

transform data repositories into consumable information, equipping users with a tool to deduce visual patterns and make effective decisions [1]. Although 2D 'dashboard-style' visualizations are commonplace, the recent resurgence of VR provokes questions about its suitability as a medium for scientific data visualization. Bryson [3] defines virtual reality as "the use of computers and human-computer interfaces to create the effect of a three-dimensional world containing interactive objects with a strong sense of three-dimensional presence". Data visualization researchers have suggested that VR's wider field of view, increased dimensionality and sense of presence could add value for analyzing scientific data, and will enable more natural and quicker exploration of large data sets (e.g. [3, 10]). In this paper we investigate whether the use of VR influences users' approaches to data exploration and the insights that they gain. Moreover, we explore how VR affects users' experience with, and understanding of, data when compared with the use of equivalent 2D visualizations. This paper contributes early insights about the utility of VR for data exploration and provides directions for future work.

VR Data Visualizations

We created two VR data visualizations, based on prior work, to explore users' experiences with data visualization in virtual environments. First, '*Be The Data*' which immerses users in a three-dimensional scatter plot, allowing them to interpret a dataset from various perspectives. Second, '*Parallel Planes*', which enables presentation of *n*-dimensional datasets and supports users in understanding relationships between each of the dimensions. Both VR visualizations were developed for Android smart phones with Google Daydream VR headsets and controllers using the Unity game development platform.

VR Be The Data

Our 'Be The Data' visualization (Figures 1-3) utilizes a three-dimensional scatter graph represented in a virtual world. Users can navigate around this environment (moving and looking freely in all three dimensions), immersing themselves in a dataset[1] to explore the visualization from various angles.

The visualization builds on an idea from Chen *et al.* [4], allowing people to embody ('be') a data point. Chen *et al.*'s study revealed that allowing students to 'Be the Data' in a physical (non-VR) space provided the necessary engagement to enable them to quickly learn about multi-dimensional data. We therefore transposed the concept of becoming a data point into a VR environment. Users were able to point and click on data points they wished to "become" using a Google Daydream controller. This shifted their position to the x,y,z location of the point, such that they could see the rest of the dataset from that perspective. Hovering the pointer over a data point without clicking would bring up a "hover box" with precise x,y,z dimension values for that point (as shown in Figure 3).

VR Parallel Planes

Our Parallel Planes visualization (Figure 4) is based on a VR visualization by Brunhart-Lupo *et al.* [2]. This is an extension of the parallel coordinates visualization [6], with an additional data dimension added in the z-axis. The visualization enables observation of relationships and trends between dimensions in a high-dimensional space through the structure of displayed lines.

[1]The dataset used to populate the Be The Data visualization contained measures of daily sleep and productivity for a participant from a self-tracking study [7]. Hence, the three dimensions were Date (DD/MM/YY), Sleep (Hours), Productive Time (Hours).

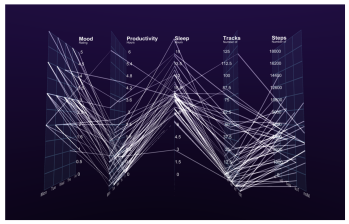

Figure 4: Parallel Planes (VR)

Figure 5: The user has brushed a region at the top of the Mood y-axis, across all days of the week (z-axis). As a result, highlighted lines emphasize values in other dimensions for all days when Mood was high.

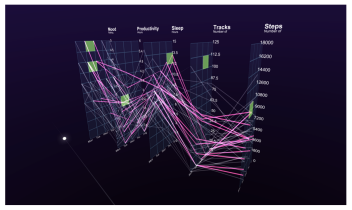

Figure 6: Parallel Planes: multiple brushed selections across planes

Each plane, spaced evenly along the x-axis, corresponds to a different dimension within a dataset[2]. The scale on each plane's y-axis corresponds to the values for the dimension. The z-axis was assigned to represent day of the week.

In terms of interactivity, users can move freely around the environment to view the visualization from different perspectives. They can also point and hover over data points using the controller to see their precise values. Selecting data points or regions of planes applies 'brushing' such that all corresponding data points are highlighted, i.e. linked values in other dimensions, or all lines that intersect the brushed regions of the plane (Figures 5 and 6).

Traditional 2D Data Visualizations

As a basis for comparing VR and 2D visualizations we created 2D data dashboard counterparts for both the Be The Data and Parallel Planes visualizations (Figures 7 and 8). These consisted of side-by-side visualizations that matched orthographic 2D projections from the VR visualizations. Hence, 2D and VR representations were informationally equivalent. They also contained comparable interactivity features, e.g. 2D visualization users were able to hover over points to see values, scroll and zoom on each graph in a similar manner to the movement functionality in the VR environment, and 'brush' to highlight lines in Parallel Planes, etc. The 2D visualizations were contained on a web page implemented using HTML, CSS and the D3.js visualization libraries and displayed on a laptop with a 15" screen at 2560x1600 resolution. A mouse was used for interactivity.

[2]As with Be The Data, we populated the Parallel Planes visualization with data from a self-tracking study [7] - Mood (Score 0-5), Productivity (Hours), Sleep (Hours), Music Listening (No. of Tracks), Physical Activity (Steps).

User Study Method

Participants

Our experiment involved 16 participants formed entirely of undergraduate students (Age: M = 21.6, SD = 0.60). All participants had good numeracy, having achieved a Grade A or above in GCE Advanced Level Mathematics (UK). The distribution of gender was 8 Female, 7 Male and 1 Prefer Not To Say. We randomly assigned 4 participants to each of the following experimental conditions: (A) 2D Be The Data, (B) 2D Parallel Planes, (C) VR Be The Data, and (D) VR Parallel Planes. This design allowed us to perform a between-subjects comparison of participants' data exploration approaches and experiences for each technology (2D and VR), across two different visualizations.

Procedure

Training Stage

In the study we included an initial training stage to allow participants to become familiar with the data visualization and its' controls. The researcher began by explaining the controls to the participant (moving, hovering, selecting, etc). Next, the researcher provided an explanation of the data included in the dataset.

Participants were introduced to a 'think-aloud protocol' and asked to verbalize their thoughts, actions and any insights gained from the data as they interacted with the technology. Participants were then invited to use the data visualization tool without time limits for exploration. Each participant finished the training stage once they felt comfortable with the controls of the visualization and the 'think aloud' approach, and they reported that they would be unable to gain any additional insight about the dataset if they were to continue.

Figure 7: Part of the 2D dashboard equivalent for the Be The Data visualization

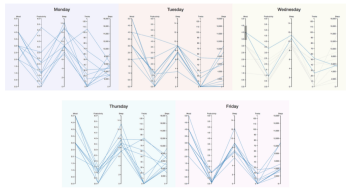

Figure 8: Part of the 2D dashboard equivalent for the Parallel Planes visualization

Figure 9: Participants interacting with the data visualizations in VR conditions.

Main Stage

In the main stage of our study, the training dataset was replaced with a different dataset to explore. This meant that there were no learning effects regarding the dataset. The same 'main stage' dataset was used for each participant. Participants were once again asked to explore the data and report any insights they gained, whilst 'thinking aloud'. As with the training stage, we placed no time limit on the participants' exploration, and instructed them to finish when they felt that they could not gain any additional insight from the data. Upon completion all participants completed the unweighted version of the NASA TLX Questionnaire [5] to measure their perceived task workload.

Analysis Method

To analyze the data obtained from the study we transcribed the participants 'think aloud' utterances from audio recordings of each session. Transcripts were then manually coded by a researcher according to existing schema taken from prior work on *insight-based* evaluations of data visualizations [8]. These coding schema included identification of:

Insights - findings relating to the data. E.g. *"This person slept much more in the earlier stages of data collection"* and *"On the final day it was only 4 hours"*.

Hypotheses - Proposed explanations made on the basis of evidence provided by the visualization. E.g. *"I think this person's sleep has an impact on their productivity"*.

Correctness - The veracity of the participants insight (as determined by the researchers); either *Correct*, *Incorrect* or *Ambiguous* where insights were subjective (e.g. *"...this person does a lot of exercise"*).

Breadth vs. Depth - *Breadth* observations provide an overview of the entire dataset (e.g. describing high-level distribution of the data). A *depth* observation is detailed, and concentrates on a small number of data points or specific individual data points.

Results

In the following sections we report the TLX measures and frequency of coded items, and compare them between the VR and 2D conditions.

Data Exploration Workload, Performance and Satisfaction

Our results reveal no significant difference in *overall workload* (all TLX dimensions combined into a single workload measure) between 2D and VR data exploration. However, a two-way ANOVA on sub-scale measurements of the TLX questionnaire (see Figure 10) revealed significant differences in 'Performance Demand', $F(1, 12) = 13.816$, $p = 0.003$, and 'Physical Demand', $F(1, 12) = 10.026$, $p = 0.008$, between 2D and VR conditions.

The Performance Demand sub-scale of the TLX captures how *successful* participants felt in performing the task, and how *satisfied* they were with their performance (n.b. higher sub-scale values correspond with increased demand). Our results reveal that participants found data exploration to be more successful and satisfying in VR (Performance Demand: $M = 28.75$, $SD = 10.26$) than in 2D (Performance Demand: $M = 54.38$, $SD = 16.13$). The sub-scale results also show that VR data exploration required significantly more Physical Demand ($M = 33.75$ $SD = 21.21$) than 2D ($M = 8.13$, $SD = 5.94$).

Insight and Hypothesis Generation

The coded transcripts allowed us to calculate the number of insights generated in each condition. A two-way ANOVA analysis of main effects revealed no significant difference in the number of insights generated when exploring data in 2D ($M = 18.63$ $SD = 8.60$) vs. VR ($M = 17.25$ $SD = 5.63$), $F(1, 12) = 0.919$, $p = 0.357$.

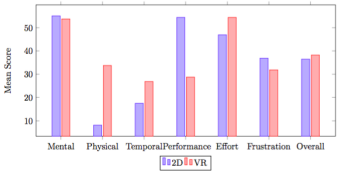

Figure 10: NASA TLX scores for 2D and VR data exploration. Higher sub-scale scores indicate greater demand.

We also tested for main effects of medium (2D vs. VR) on the correctness of insights, using the *Correct* and *Incorrect* codes. We found no significant main effect of medium on the number of correct insights reported, $F(1, 12) = 3.488$, $p = 0.086$. However, there was a significant main effect of medium on the number of incorrect insights reported, $F(1, 12) = 34.57$, $p < 0.001$. Participants reported fewer incorrect insights in VR ($M = 0.63$ $SD = 0.52$) than with 2D ($M = 3.38$, $SD = 1.85$).

We found no significant main effect of medium on the number of hypotheses generated, $F(1, 12) = 0.046$, $p = 0.834$.

Depth of Data Exploration
Our analysis revealed a statistically significant main effect of medium (2D vs. VR) on the 'depth' of insights (whether insights related to specific data points or the dataset as a whole), $F(1, 12) = 4.856$, $p = 0.048$. We found that participants reported fewer 'deep' insights with VR visualizations ($M = 6.13$ $SD = 3.482$) compared with the traditional 2D visualizations ($M = 8.00$ $SD = 7.111$). There was no significant effect of medium on the number of 'breadth' insights reported, $F(1, 12) = 0.1$, $p = 0.757$.

Discussion and Future Work

This study provided an insight- and workload-based comparison of data exploration in VR and 2D. We found that there is no difference in the overall data exploration workload between mediums. Although there is a difference in physical demand, this is unsurprising given the requirement for a greater degree of physical movement in VR. Notably, many of the participants opted to use the VR device whilst standing (Figure 9), whereas participants were all seated when using the 2D visualizations.

A promising result for the VR visualization tool is that participants rated their performance workload as lower (corresponding to increased feelings of success and satisfaction), compared with participants in 2D conditions. Previous work has shown that a high level of perceived presence (*"a sense of being there"*) is closely associated with increased satisfaction and an appealing experience [9], which may provide an explanation for this finding.

While participants reported the same number of insights and hypotheses using both mediums, a compelling finding from our study is that participants reported fewer inaccurate insights when using the VR visualizations. Our work so far does not provide a definitive explanation for this, however one possible rationale is that users are more attentive and meticulous in their analysis as a consequence of being more satisfied and engaged by the VR technology. It is also possible that the novelty of viewing data in VR resulted in more interactions with the data, including a greater degree of checking or verifying the insights that participants reported.

Although we transposed the concept of *becoming* a data point (from [4]) into a VR environment, many participants did not use this functionality. We observed all participants temporarily orientating themselves to produce orthographic projections of the data in VR, thus negating the three-dimensional aspect of the visualization. A lack of precision associated with interpreting the exact positions of data points in 3D 'at a glance' (without hovering to check values) may have led to participants being less focused on *deep* insights (relating to individual or small numbers of points) than general, breadth-based insights relating to the entire dataset. However, our workload results reveal that there was no difference in mental demand, effort or frustration to suggest that VR had any significant disadvantages. Future work may wish

to investigate the impact of embedding 2D visualizations into virtual environments to capitalize on the engaging effects of VR, whilst overcoming possible limitations of 3D representations.

Overall, VR data exploration was perceived as satisfying, successful and resulted in fewer inaccurate insights. These results suggest that VR may help to engage people in effective data analysis. We therefore see potential for VR in application areas such as personal informatics and self-tracking, which often involve the collection of multi-dimensional data and require users' to actively engage in analysis and reflection with their data [7].

Our findings so far should be interpreted with appropriate consideration of the small sample size in our initial study. We aim to expand our investigation in our ongoing work, evaluating the visualizations with more participants and incorporating more fine-grained analysis of insights (e.g. including coding of sub-categories of insight that differentiate between identification of *outliers*, *trends*, *distributions*, etc.). We are also interested in adapting our VR visualization tools to enable collaborative, multi-user data exploration and to explore the impact of VR on collaborative analytics tasks, in comparison with traditional 2D visualizations.

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