Supporting Reflective Learning For Daily Activities Using An Interactive Dashboard

Margreet Riphagen
margreetriphagen@gmail.com
Master Information Studies, Human Centered Multimedia,
University of Amsterdam, Faculty of Science

ABSTRACT

This paper presents the motivation, design and evaluation of an interactive dashboard, supporting reflective learning for daily activities. Based on gathering data from a 4-week field trial in which 24 participants used a Fitbit and a GPS tracker, design and interaction recommendations were made by taking the Fitbit dashboard as a starting point. A dashboard was developed according to the visual analytics model proposed by Keim, Mansmann, Schneidewind, Thomas, and Ziegler (2008). This model describes the iterative process of data gathering and exploration, hypothesis building, visualization design and analysis, and the gaining of insight by directly interacting with the gathered data. This study aims to evaluate the effectiveness of using a visual analytics tool to facilitate insight into how this daily physical activity data yields to reflective learning, also known as learning by returning to and evaluating past work performances and personal experiences in order to promote continuous learning and improve future experiences (Boud, 1985).

Keywords

Visual Analytics, Reflective Learning, Interactive Visual Analytics Dashboard, Fitbit, GPS Tracking

1. INTRODUCTION

During the past five years people all over the world have been recording data about themselves and their surroundings (self-tracking), producing a flux of information with accelerometers. Technology, such as accelerometers, can be supportive in this process and very useful in assisting people with increasing their physical activity. These can objectively capture body movement and provide information on the total amount, intensity, duration and frequency of physical activities performed, in order to motivate people to improve their life. However, with the increasing amount of generated and collected data available, the efficiency of their use becomes more challenging. As a consequence, applying accelerometry as a tool to assess daily physical activities is a rapidly evolving field of research.

This research focuses on daily activity data, specifically, involving walking. Walking is the most frequently reported type of leisure-time physical activity (Rafferty, Reeves, McGee, Pivarnik, et al., 2002). Although walking is important to our daily lives, we have little understanding about how much people walk outside leisure-time contexts. And how many steps per day does an average person make? According to Tudor – Locke (Ph.D. Department of Exercise and Wellness) and Bassett Jr. (Ph.D. Department of Health and Exercise Science) men have an average of 7192 steps per day and women have an average of 5210 steps per day. The global increase in overweight and obesity is attributable to a trend towards decreased levels of physical activity (Burns, Lueg, & Berkovsky, 2012). By making people aware of their sedentary behavior, they might want to learn from it, reflect and change it (Consolvo et al., 2008).

With the far-flung availability of cheaper self-trackers and Global Positioning System (GPS) trackers it is possible not only to record the numbers of steps but also people's movement. But while these data contain relevant knowledge, within a context they lack the appropriate semantic embedding which makes automatic algorithmic analysis possible (Andrienko, Andrienko, & Wrobel, 2007).

The history of self-tracking using wearable sensors in combination with wearable computing and wireless communication exists already since many years, and also appeared, in the form of sousveillance already in the 1970s (Mann, 2001, 1998). This study aims to show that Quantified Self (QS) approaches can support reflective learning processes. The Quantified Self uses various self-tracking methods to 'quantify' a persons approach to life and goals, often helping to see where things are

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changing, or need to change, to track progress around personal endeavors, in order to personalize our lives.

The Fitbit[1], a wireless activity tracker, (also see Section 11) can be seen as a first generation of self-trackers that can be 'dressed' with covers and ornamentation, for example, footwear covers for bicycling, or watertight wristband covers for swimming. Devices like this produce data at an incredible rate, leading to a significant information overload and new requirements for the analysis process. *Visual Analytics* (Keim et al., 2008) could be a solution.

Visual analytics (VA) can be described as 'the science of analytical reasoning facilitated by interactive visual interfaces'. To be more precise, visual analytics is an iterative process that involves information gathering, data preprocessing, knowledge representation, interaction and decision-making, by combining the analytic capabilities of the computer and the abilities of the human analyst (Thomas & Cook, 2005). Visual analytics seems an ideal solution for the information overload problem and for facilitating the Quantified Self community's data analysis.

This study was conducted according to the visual analytics model proposed by Keim et al. (2008) (Figure 1), in order to turn data information overload into an opportunity. This model describes the iterative process of data gathering and exploration, hypothesis building, visualization design and analysis, and the gaining of insight by directly interacting with the gathered data, in order to reflect upon the data.

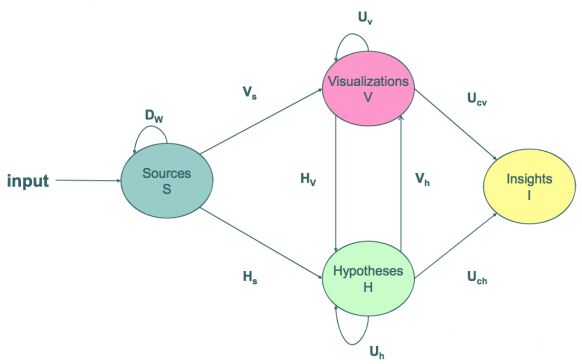

Figure 1: Keim et al. (2008) *processing of data* model that describes the iterative process of VA and the interaction between Sources *(S)*, Visualizations *(V)*, Hypotheses *(H)* and Insights *(I)*.

Visual analytics focuses on managing big volumes of information by integrating human judgment through using visual representations and interaction techniques in the analysis process. Analysis of these massive volumes of data is a place of deciding for various domains, e.g. decision-makers, analysts, or in another sense, people interested in rapidly gaining insight from this flood of data. As raw data in most applications have little value themself, we want to be able to extract the information contained in it, moreover interact with it, learn from it and thereafter reflect on it.

The objective of this study is to evaluate the effectiveness of using a visual analytics tool to facilitate insight into how this daily physical activity data yields to reflective learning, also known as learning by returning to and evaluating past work performances and personal experiences in order to promote continuous learning and personal future experiences (Boud, 1985).

2. RELATED WORK

In this section we consider a more in-depth reading of self-tracking, other visual analytical tools, reflective learning, visualizations, dashboards, and lastly, analytical interaction and navigation for effective analysis.

2.1 Self-tracking

Self-tracking devices, like sensors, smart phones/tablets etc. increasingly helps individuals gain more insight int the physical aspects of their lives. Recent advances in small inexpensive sensors and low-power processing have enabled new technologies that use on-body sensing and machine learning to automatically track and figure out people's activities throughout the day (Consolvo et al., 2008). Since the introduction of the Quantified Self by Gary Wolf and Kevin Kelly a few years ago, increasingly more people are using such self-tracking tools and collecting data via devices such as Fitbit, or Jawbone UP[2]. Jawbone UP consists of a wrist-worn motion detector that interfaces with an iPhone app, allowing the user to track his/her daily physical activity. Stand-alone wearable tracking devices, like Fitbit, but also the Nike Fuelband[3] and the Misfit Shine[4], are self-monitoring devices that display visualizations of the physical activity and behavior of its user.

Keeping track of body/physical conditions is nothing new. For example, many athletes have been carefully and precisely monitoring personal metrics for decades. The power of self-tracking moreover, is even more profound. Collecting data can help to change behavior by using self-tracking tools. Feedback loops can be established (McClusky, 2009), because when we keep track of something we see how the data matches up with what we would like to happen, and we can use that knowledge to modify our actions. The effect of feedback on attempts

[1] http://www.fitbit.com/zip

[2] `https://jawbone.com/up`.

[3] `http://www.nike.com/us/en_us/lp/nikeplus-fuelband` .

[4] `http://www.misfitwearables.com` .

to change behavior is well accomplished. DiClemente, Marinilli, Singh, and Bellino (2001) state that personalized feedback increases the effectiveness from exercise programs to interventions for problem drinkers. Feedback is important and powerful. This feedback can also be internal, as one gets positive feedback from their body after a couple of runs. The ease with which these new tools make self-tracking possible combined with the increasing possibilities of sharing data and gaining more insight from this data, results in more and more people finding it useful to quantify their lives.

Self-tracking plays an extensive role as it aims at presenting the application of visual analytics for analysis of daily activity data, and therefore it can have a new full impact on the visual analytics process. This experiment is an attempt to perpetuate the purpose of visual analytics in analyzing these data.

2.2 Visual Analytic tools

Only a few studies have been conducted towards the utility of visual analytic tools for data analysis. Bier, Card, and Bodnar (2008) assessed the suitability of their Entity Workspace System in the context of design guidelines for collaborative analysis. The system was modified based on five design guidelines and evaluated it. They confirmed positive effects of the tool on collaboration and the usefulness of the design guidelines for collaborative analysis. Perer and Shneiderman (2008) studied the effectiveness of their system SocialAction. A long-term case study combined with in-depth interviews offered an evaluation confirming the core value of SocialAction - integrating statistics with visualization - and further provided guidance for redesign of the tool. Lastly, Kang, Gorg, and Stasko (2009) conducted an evaluation of the visual analytics system Jigsaw, and compared its use to three other more traditional methods of analysis. Two aspects of Jigsaw turned out to be helpful; showing connections between entities and narrowing down the focus. Aforementioned related works provide valuable implications to change design directions for future analysis support tools, as proposed in this research.

2.3 Reflective learning

According to Boud (1985), reflective learning is learning by returning to and evaluating past work performances and personal experiences in order to promote continuous learning and improve future experiences. But a consolidated model that describes the role of technologies, such as Fitbit, is missing out on reflecting (Rivera-Pelayo, Zacharias, Müller, & Braun, 2012). Our growing interest in self-tracking results in a mixture of tools to gather data in order to self-reflect and monitor ourselves, with the aim of knowing more about our own habits, behavior and recurrent patterns. QS approaches are more pragmatic, whereas reflective learning is driven by theories. Figure 2 shows a model for the technological support of reflective learning centered on the model of Rivera-Pelayo et al. (2012).

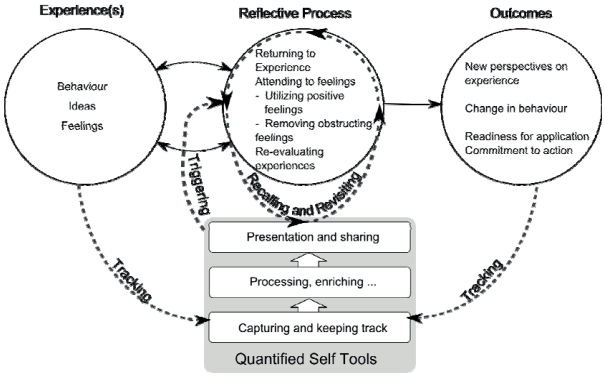

Figure 2: Rivera-Pelayo et al. (2012) model that shows the role of the three QS potentials in the process of reflective learning.

This model shows how QS approaches can reinforce the process of learning by reflection and alter the design of new QS tools for informal learning purposes.

Technology can be used as a tool and be supportive in providing resources for reflection. The user can be enabled to see things from multiple perspectives and be guided in the process of reflection. A record of events can be looked at several times. Moreover, technology allows one to see more than one could possibly see without. Sensor technologies record, detect and represent data of experiences otherwise not available to human perception. Thus reflecting upon these events will let you experience a different viewpoint out of one's own scope.

2.4 Visualizations

Reflection is possible through interacting with the specific data represented in a visualization. But transformation of data into significant visualizations is not an easy task that will automatically improve through steadily growing computational resources. Visualizations, as it applies to visual representations of information, can be preceded by three words, with different meanings (Few, 2009): data visualization, information visualization and scientific visualization.

Whereas Few uses *data visualization* as an umbrella to cover all types of visual representations that support exploration, examination, and communication of data, *scientific visualization* techniques cover accurate visualizations of the real world, and *information visualization* techniques cover visualization of concepts that often are abstract in nature.

Data such as Fitbit is typically scientific data, and can be represented in many different ways but it is still unclear which one is the best (Keim et al., 2008). Also, Keim et al. (2008) argue that state-of-the-art concepts

of representation, perception, interaction and decision-making need to be applied and extended further to be suitable for visual data analysis.

VA makes it possible to find patterns in this enormous amount of data and makes it more understandable by turning it into visual patterns. Human beings are programmed to understand visual information better than words or numbers, especially when presented via a dashboard.

2.5 Dashboard

A dashboard is a visual display of the most important information needed to achieve one or more objectives, consolidated and arranged on a single screen so the information can be monitored at a glance (Few, 2006): a possible solution for the information overload problem. A dashboard is something like a dashboard in a car; it displays the most important information with the ease of one look. In a car, you want to know the speed, how much fuel is left in the tank, and if there is something wrong with the car. Information like how much brake fluid is present, is only relevant when it is below a certain threshold.

A performance dashboard is an information system that is able to collect and present data from various sources in such a way that the user can see several performance indicators. There is little written in academic journals on the topic of dashboards, though there are some books available (Few, 2006), and (Rasmussen, Bansal, & Chen, 2009). Despite their tremendous popularity and potential, many and perhaps most dashboard implementations fail miserably. A dashboard's entire purpose is to communicate important information clearly, accurately, and efficiently, but most dashboards say too little, and what they do say requires far too much effort to discern.

In general, dashboards try to consolidate all information onto a single screen. This single-screen display must provide the overview that is needed when an action is required, and ideally should provide an easy gateway to any additional information that is needed to determine the precise action that is appropriate.

2.6 Analytical interaction and navigation

As mentioned before, to really get insight into the data, a system should provide different means of interacting with it. Human-computer interaction (HCI) is the research area that studies the interaction between people and computers. It involves the design, implementation and evaluation of interactive systems in the context of the user's task (Dix, Finlay, Abowd, & Beale, 2003). Visual analytics combines the advantages of machines with the strength of humans, such as analysis, intuition, problem solving and visual perception. The human plays a central role in this process and HCI is a key component for supporting knowledge discovery.

There is not one way to navigate through all the gathered data, though some navigational strategies can be extremely helpful. Analytical navigation can be divided in two approaches, Few (2009): *directed* and *exploratory*. Whereas directed begins with a specific question we hope to answer, with exploratory analysis we start looking at the data without predetermining what we might find. When something abnormal has been found, viewers switch from broad awareness to close observation and analysis. A useful starting point for designing advanced graphical user interfaces is the Visual Information-Seeking Mantra: overview first, zoom and filter, then details on demand; tasks usually performed by users when navigating information visualizations design (Shneiderman, 1996), one of the most notable researchers in this field.

The effectiveness of information visualization hinges on two things: clear and accurate representing information and the human's ability to interact with it to figure out what the information actually means. Representation has its roots in computer graphics. Interaction involves the dialogue between the user and the system, as the user explores the dataset to uncover insights. Takatalo et al. (2008) states that its ultimate goal should be to hide complexity details from users and provide an environment for knowledge discovery through an outstanding human experience.

Thomas and Cook (2005) state that visual representations alone cannot satisfy analytical needs. To support the dialogue between the analyst and the data, interaction techniques are necessary. And not just common interactions such as search techniques, but more sophisticated interactions are needed to support the analytical reasoning process. The information visualization community has begun to distinguish low-level interactions (those between the user and the software interface) and high-level interactions (those between the user and the information space) (Pike, Stasko, Chang, & O'Connell, 2009). In higher-level interaction, the user's goal is to generate understanding. Yi, Kang, Stasko, and Jacko (2007) defined a taxonomy for these ways to interact with a system: Select (or brushing), Explore, Reconfigure, Encode, Abstract/Elaborate, Filter and Connect (or Linking). Whereas Few (2009) defines 13 types of lower-level interaction: comparing, sorting, adding variables, filtering, highlighting, aggregating, re-expressing, re-visualizing, zooming and panning, re-scaling, accessing details on demand, annotating and bookmarking. Here the user's goal is often to change the representation to uncover patterns, relationships, trends or other features.

This study aims to evaluate the effectiveness of using an interactive visual analytics dashboard to facilitate insight into how daily physical activity yields to reflective learning.

3. RESEARCH QUESTION

What can the various devices for capturing our activities and the programs to analyze them actually tell us? What our habits are? These are all factors that influence our everyday behavior, our minds and our psyches: what if we were able to control them, or even manipulate them? Are we then able to optimize our experiences and gain more insight in order to have, for example, a more active or vivid life, and thus reflect on it?

The proposed research is based on the before-mentioned literature and investigates whether a Fitbit in combination with a GPS tracker are able to assist people in increasing their physical activity, by reflective learning: by raising awareness of people's sedentary behavior, and learning by returning to and evaluating past work performances and personal experiences. This in order to promote continuous learning and improve future experiences. Moreover, it aims at evaluating the effectiveness of using visual analytics tools to facilitate insight into how this daily physical activity data yields to reflective learning, and improve future experiences.

Therefore the following research question is stated:
'How to present the analysis of Fitbit data for its users in such a way that it allows them to gain optimal insight, in order to assist them in increasing their physical activity and reflect upon it?

The following section will elaborate on how this study has been performed.

4. METHODS

This study was conducted according to the visual analytics model proposed by Keim et al. (2008). This model describes the iterative process of data gathering and exploration, hypothesis building, visualization design and analysis, and the gaining of insight (Figure 1).

To find out how to present analysis of Fitbit data for its user to gain optimal insight, both quantitative and qualitative research were conducted. This started with looking at Few (2006) which highlights the 13 most common design mistakes made when designing dashboards, because most dashboards fail to communicate efficiently and effectively, because of poorly designed implementations (Section 2).

4.1 Study design

24 participants, 13 staff members and 11 students, of which 14 were female and 10 were male, aged 19-68 *(M=35.1)*, were recruited through convenience sampling (Bryman, 2012). All HvA affiliated participants, from all seven domains, were given a unique number from 0 to 23 to easily distinguish them while processing the data and to prevent privacy invasion in terms of anonymity.

During a period of two months, 24 students, teachers and support staff from the seven domains of the Amsterdam University of Applied Sciences (HvA) were monitored for this experiment.

From the beginning of February till the end of March the participants carried a Fitbit Zip (an always-on electronic pedometer, that in addition to counting steps also displays distance traveled, calories burned, current intensity, and time of day) with them. Furthermore, for a period of two weeks within those two months, they also carried a GPS Canmore GT-750(L) Bluetooth tracker (a device to determine the precise location of a person, or another asset to which it is attached and to record the position of the asset at regular intervals). In the end, all movements were analyzed and collected, thereafter presented on a interactive visual analytics dashboard, in order to see if there were recognizable patterns amongst the participants, and to see if using these Quantified Self tools leads to gaining more insight from the gathered data in order to reflect upon, and create awareness for a more active lifestyle. With this information, it is also possible to see how Keim and Rivera-Peloya's models can be mapped on the collected data.

4.2 Materials

In order to answer the research question both quantitative and qualitative research was performed. There are several research instruments: the step counts from the Fitbit ZIP, the tracking of the GPS tracker (for more detailed information see the used devices Section 11). Lastly, some small interviews were conducted to gain more an idea of what data is desirable, at an interactive visual analytics dashboard, for gaining insight. Before giving out the Fitbit ZIP and the GPS tracker to the participants a questionnaire was conducted. General information about age and area where the participants live was gathered. Also questions about the participants' media usage, how they travel between various locations, and some questions about, if, and what kind of sports they are doing.

5. DATA SOURCES

A good dataset has several characteristics such as: high volume, of known pedigree, multivariate, etc. This experiment consists of two main datasets that have the above-mentioned characteristics:

1. Fitbit data;
2. GPS data.

5.1 Data gathering and processing

These two datasets have different characteristics and need to be processed in different ways. Each dataset has been retrieved from it's respective sources and thereafter processed so that it could be analyzed using Tableau

Table 1: Fitbit data and its contents. Each variable is associated with a participant.

Data file	Data	Type
`timestamp`	timestamp	Ratio
`steps`	amount of steps	Ratio
`id`	user id	Ratio
`gender`	gender	Nominal

Desktop[5] and Google Earth[6] (free version 7.0.2.8).

5.2 Fitbit dataset

The Fitibit dataset consists of a plain text data file, listing timestamps for each specific user. The overall list of timestamps contains 60,055 entries, after removal of entries where no steps where counted. Of all participants the data from the 1st of February 2013 until the 28th of February 2013 was used. The Fitbit API[7] was used to download the specific content.

An overview of the types of data that are listed for each of the data files can be found in Table 1.

Timestamp Timestamps are used as a sequence of characters or encoded information identifying when a certain event occurred, an indication for behavior;

Steps Some participants are more active than others. Assuming that making more steps means that people are more aware of their sedentary behavior, this could affect people's physical activity;

Id While not that interesting for high-level analysis, including the id's in visualizations may aid us as it allows for verifying findings with other sources and zooming in to a specific user in a later stage, for example, by conducting an interview afterwards;

Gender It would be interesting to research whether there is a significant difference in gender to see if there is a disparity in the number of steps taken between men and women.

5.3 GPS dataset

One person was removed from the original dataset due to the Netherlands scope of this research. This person was living in India, Bangalore at the moment of the research. Therefore the GPS dataset consists in the end of positions of 23 participants, which have been GPS-tracked ranging from February to March, 2013. Within this timeframe, for each participant, one week was chosen at random.

[5]http://www.tableausoftware.com/.
[6]http://earth.google.com/.
[7]`http://dev.fitbit.com/`.

Each record in the database includes the date and time, the latitude, longitude and altitude of the position and a few additional fields such as index, line ID. The temporal space of the records is every 10 seconds.

To facilitate analysis of movement data, initial prepocessing in the data was performed. The Andrienko et al. (2007) approach for analysis of movement data has been used. Sequences of records corresponding to absence of movement, i.e. where the distance in space to the next recorded position is below a threshold, were removed. The remaining dataset had exact 17,777 positions left. Furthermore the timestamp was initially set to GMT+1:00, this was adjusted to GMT+2:00.

5.4 Data Analysis and Visualization

The Fitbit analyses were made primarily using Tableau Desktop, a software application that allows interactive visualizations of data to be easily created using a drag-and-drop interface. In the patterns that emerge from reviewing the collected data of the participants, one should be able to see if users can learn from their gathered data and reflect upon it.

Furthermore, Google Earth has been used as a virtual globe, map and geographical information program. It is one of a growing number of geobrowsers, widely employed for the visual synthesis of spatial data and for interacting with these data (Wood, Dykes, Slingsby, & Clarke, 2007). The data was specified in a KML format, an XML markup language in which graphical encoding and interactions can be defined for interpretation.

5.5 Fitbit

We chose the Fitbit online dashboard[8] as a sinking point for this study; it is based on Fitbit data. Having a closer look at the dashboard, also available for mobile, it provides real-time access to statistics and is organized into tiles which can be rearranged and configured to show the user exactly what he or she wants to see. One can add, delete, and rearrange tiles of information. Available tiles include an intraday activity graph, calories burned, distance, friends, steps, very active minutes, and more. Additionally one can view daily, weekly, monthly and yearly totals and graphs for steps, distance, floors climbed, calories burned, active time, sleep quality and weight. Figure 3 represents an overview of a Fitbit dashboard with a relatively high activity of a user.

A closer analysis of the used Fitbit dashboard (see Figure 3) shows that at least 7 of the 13 design mistakes developed by Few (2006) were made in our opinion. Below a list of what the design mistakes contain and in some cases a suggestion of how a different design can easily resolve these issues. For a complete overview of the 13 common design mistakes see Section 12.

[8]http://www.fitbit.com/.

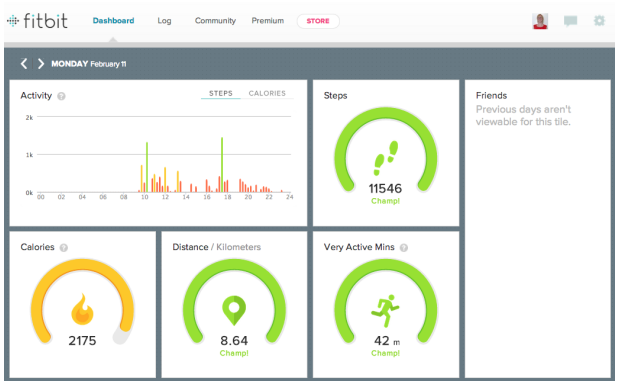

Figure 3: Overview of Fitbit Dashboard with high activity.

Supplying inadequate context for the data - Dashboards primarily exist of quantitative measures of what is actually happening. They seldom do well unaccompanied; they need a good supporting cast to get a message across. For example Figure 3 gives a total of 11,546 steps without any contextual meaning. Is this good or bad? The dashboard says *champ*. This measure of what is currently going on could be enriched by providing one or more comparative measures, such as friend's amount of steps or some history. Or at least a scale on what *champ* is based on. A quantitative scale on a graph could be really helpful here as well.
Expressing measures indirectly - To be able to express measures suitably one must understand precisely what the user needs to see and what he/she wants to get out of this information. For a measure to be meaningful, viewers must know what is being measured and in which context the measures are being expressed. A measure is poorly expressed if it fails to directly, clearly, and efficiently communicate the meaning that the dashboard viewer must recognize (Few, 2006). For example in Figure 3 it is not immediately clear what is being represented in the x-axis in the *Activity* tile. To get more feedback out of the activity overview, it could be displayed more directly and vividly by encoding a daily average (measured over time) as a reference line of 0% and the variance as a line that meanders above and below average, expressed in units of positive and negative percentages. Also when a user is making less steps and only reaches half the 'horseshoe' (see other tiles) nothing is being displayed.
Choosing inappropriate media of display - Choosing the inappropriate media is one of the most common design mistakes. Using a pie when a table would work better is a common mistake. The detailed amount of steps in Figure 3 indicates that the user reached the maximum number of steps to be made (in a day / week or maybe even years?), as the 'horseshoe' image is completely full (see *Steps* tile). And what to think of the used colors. Both green and mint green are being used, as well as yellow and red. But what do they mean? The graph cannot be interpreted in a useful way with just this information, so what use is the picture?
Using poorly designed display media - After it has been decided what to display, it should also be designed in such a way that it is shown clearly and efficiently, without any distraction. As mentioned before in Figure 3 the use of the two green colors is confusing. And why do they choose a 'horseshoe' figure, instead of for example a bar chart?
Encoding quantitative data inaccurately - The images used should precisely communicate the values so you can compare them to one another as a means of comparing the values and understanding the relationships. This has not been clearly executed in Figure 3.
Arranging the data poorly - The current dashboard of the Fitbit works with tiles. We are of the opinion that the tiles are not arranged in a proper way to get the most out of it. An addition here could be a comparison with other days of that week, or other moments that month when doing the same exercise, e.g. running.
Ineffectively highlighting what's important - The Fitbit dashbaord is making incorrect use of highlighting. All the tiles in this dashboard are visually prominent and vying for the user's attention. When this happens a dashboard has failed.

6. DESIGN

As mentioned before, to really get insight from the data, a system should provide different means of interacting with the data. Two elements play a crucial role here: *representation* and *interaction*. Representation has its roots in computer graphics. Interaction involves the dialogue between the user and the system, as the user explores the dataset to uncover insights. Our main target audience is Fitbit users, or in another sense, people who want to reflect on every day activities.

Nowadays only a few software tools are available to organize big amounts of data, to create overviews and to explore them proposing useful insights. However, most of these systems have become obsolete in terms of interaction, let alone using interaction techniques like Yi et al. (2007) suggest (see also Section 2). Aforementioned interaction techniques are integrated in an interaction model Figure 4. This model describes the relation between each interaction of the user with the system, as well as how different stages of exploring the data are connected by the various interactions, with the goal to visualize a design, to analyze and gain further insight.

We designed an interactive visual analytics dashboard for the Fitbit user, including Few (2006) 7 design mistakes (see Section 5). This dashboard also integrates Shneiderman's visual information seeking mantra Section 2. Multiple visualizations have been integrated into the dashboard system to use all functions and opportunities of various visualizations and improve the Fitbit user's data exploration and analysis process. After ini-

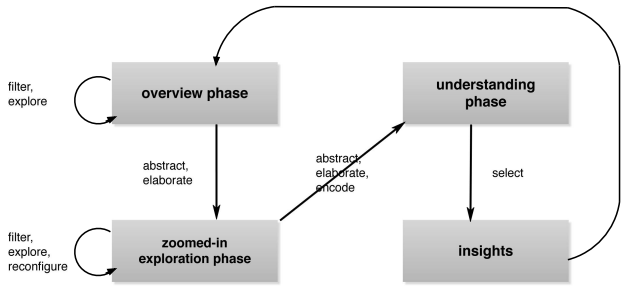

Figure 4: Interaction model with high-level interactions used during VA process.

tial user feedback, some adjustments were made for several visualizations to meet users' analysis needs and goals. Advanced techniques like zooming, filtering, and details on demand are offered. The dashboard's design is related together in such a way that users' interactions with one view will have a continued effect on other views. This benefits the user in that it allows him/her to gain optimal insight in order to increase physical activity and reflect upon it.

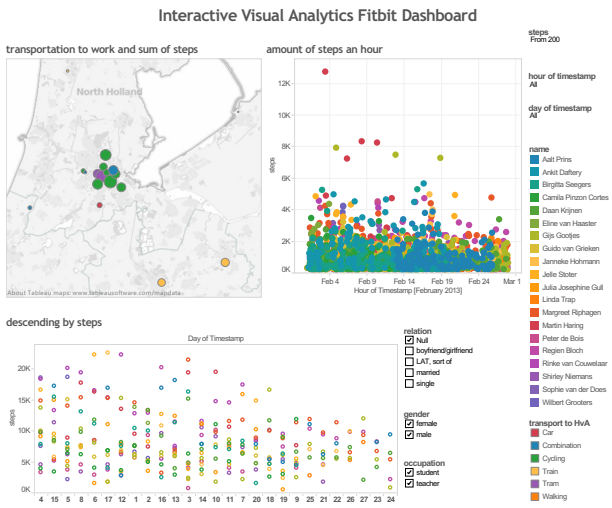

Figure 5: Interactive Visual Analytics Dashboards.

As shown in figure Figure 5, the interactive VA dashboard combines multiple views to efficiently describe the gathered Fitbit and GPS data. Firstly a geo-spatial overview is given where participants are living and what kind of transport they use for commuting. The color represents a different form of transportation (car/cycling/train/tram/walking or a combination/), where the size of the circle shows the sum of the steps taken. On the right sight of the dashboard an overview is given of the amount of steps an hour for each participant (all in a different color). Additionally in the bottom of the dashboard the user can find more information about the sum of steps a week, day or hour. The sum of steps filter includes greater than or equal to 200 steps. Furthermore the dashboard can be filtered on gender (male/female), occupation (teacher/student) and relation (married/LAT/single/boyfriend or girlfriend).

Few (2006) state that a dashboard is defined as a comprehensive visual representation of the most relevant information required for users to reach specific goals. The ideal interactive visual analytics Fitbit dashboard embraces even more than visualized in Figure 5. Based on the conducted interviews users would also be interested in gaining more insights about their daily activity in combination with the weather forecasts. P24: *"I definitely would like to be interested in seeing my daily activity in relation with the weather, this to know when to set my goals for a specific day in the week"*. This insight could be useful when someone is setting his/her weekly goals, then it is definitely relevant to keep an eye on the weather. Another area of interest was gaining more insight in the altitude in relation to walking(routes). P11: *"I am a frequent runner and I would be interesting to gain more insight in the height of the roads. Imagine San Francisco, where they mapped several biking routes, which indicates the grade of a street, so you can avoid the steep hills, or take the challenge"*. Another suggestion from one of the participants would be, to intensify the forming of peer groups, rank yourself against peers for various different purposes, i.e. competition, stimulation, etc, to share experiences with one another. One of the interviewed participants suggested it would be interesting to include animations. P03: *"I would be interested in a combination of the Fitbit and something like Google Location History*[9]*"*. It is debatable whether this really has an added value to the dashboard, but this is perhaps more a *'nice to have'*.

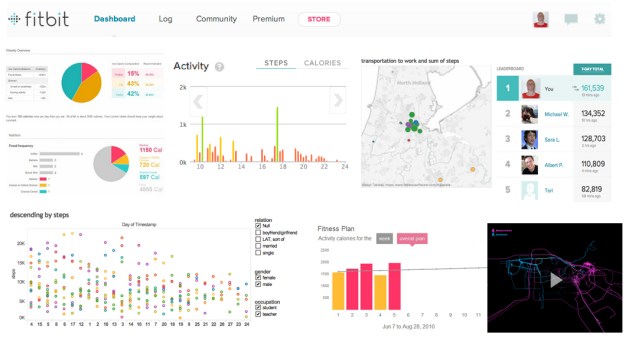

Figure 6: Interactive Visual Analytics Fitbit Dashboards.

After another iteration of user feedback the dashboard as presented in Figure 6 was designed. This dashboard has all benefits (Shneiderman's visual information seeking mantra and Few's 7 design mistakes) and visualizations

[9]https://maps.google.com/locationhistory/.

from the dashboard shown in Figure 5. But in addition, with this interactive VA dashboard it is possible to gain insight in the amount of calories burned, this in relation with food consumption. The user can see his/her activity per hour in the form of bar chart. Also an activity overview of friends can be seen, a quick overview of targets are represented and lastly an animated GPS track of Fitbit friends is shown.

7. DISCUSSION

Based on the gathered Fitbit and GPS data a redesign was made for the Fitbit dashboard. In our opinion this interactive visual analytics dashboard increasingly meets the real needs of the Fitbit user, and is capable of assisting the user in increasing his/her physical activity and to reflect upon it. Nevertheless, it is advisable to evaluate this dashboard iteratively with new users, to see where it needs further improvement.

One of the ways in which the visualizations can be evaluated is by performing benchmark tasks. According to North (2006) this method's fundamental concept is to change the benchmark tasks from an independent to a dependent variable. This suggests that users are more free to explore the given visualizations; they are not instructed what to explore or what information to select. Thereafter the user will attempt to find a way to answer the questions. Insights that are gathered from each user might have a large variation within the same clusters.

It is good to appoint out that the gathered Fitbit data consists of a certain timeframe, namely the month of February. In order to make a more thorough analysis, the dataset should include a longer timeframe as well as in various seasons. This would allow us to identify patterns over a longer period, and take this insight into account in redesigning the Fitbit dashboard. Also, some participants stopped using the Fitbit after a couple of days. The next experiment should take drop-outs into account. Furthermore, the GPS trackers were also used for a relatively short period of time (one week). If used for a longer time, this would allow us to identify patterns over a longer period.

Assuming that QS tools can be pointed out to assist people in realizing their desired outcomes, there will always be a lack of understanding on how to identify the various situations and context in which they will be used.

8. CONCLUSION

In this paper we described the realization of an interactive visual analytics dashboard using Fitbit's daily activity data. A dashboard (Figure 6) that is better capable of supporting reflective learning than the dashboard in Figure 3. As better insight can be gained based on the represented visuals. This research was done to gain insight into which of this data is relevant for reflective learning, for a Fitbit user, in order to promote continuous learning and improve future experiences. Only little research has been done on the use of Fitbits widely, as well as reflective learning in combination with a QS tool, because it is still a relatively young technology. The collection of daily activity data through QS approaches offers a rich source of data that has not been available for learning processes before.

This paper set out to explain what dashboards are, the drivers and obstacles to their adoption, and where research is needed to fully exploit their potential. The last years the development of QS tools has been triggered by their fast growth, such as the Fitbit and Nike Fuelband.

In conclusion, the results of this study emphasize the importance of a dialogue between the analysts and self-tracking users in the analytical process to feat visual analytics tools. Additionally iteratively enhance the analytical process supported by visual analytics, in order to filter and customize the visualizations at ones preference. We see the future rosy, the data world is still very much in its infancy, and the debate about what it is exactly, where it is going, and how everyone will get there, has just started.

We hope that our contribution, in the form of a redesign, will give awareness to, and understanding of dashboards, and will induce more research. We believe that visual analytic tools can help reflective learning for daily activity properly.

9. FUTURE WORK

Future work involves the design and implementation of new QS tools that will empirically validate the presented model (Figure 2) to support reflective learning. Also future work can include further optimization of the created dashboard. It is an iterative process, which is continuously exposed to new developments. It could also include further unrolling of the dashboard in other domains and areas within self-tracking, including Nike and Jawbone. Also the use of external data sets (such as historic weather data) can be exciting to explore further. Besides further heuristic evaluations of the VA tools into daily analytical activities of self-tracking can be conducted, to provide a user with enough information in order to promote continuous learning and improve future experiences.

10. ACKNOWLEDGEMENTS

The authors would like to thank Marcel Worring for his valuable feedback as supervisor to this study. Additionally, we would like to thank our participants for generously sharing their data with us and reviewing the interactive visual analytics dashboard, and lastly the anonymous reviewers who provided feedback on our work.

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11. APPENDIX USED HARDWARE

11.1 Fitbit ZIP

This wireless activity tracker exists of a Zip, wireless sync dongle, battery, battery tool and a clip to attach it to you. It tracks ones daily activity, syncs data realtime to a computer or smartphone, and one can check his/her progress, steps taken, calories burned distance traveled. It uses a three-dimensional motion sensing technology similar to the device that is used in the Nintendo Wii.

The Fitbit is made of silicone and a metal clip, wireless sync dongle to mobile and laptop, replaceable battery, LCD (liquid crystal display). There is tap control of the device, it is both Windows and Mac compatible, and the battery life is 4-6 months. The Zip uses a MEMS 3-axis accelerometer that measures motion patterns to determine calories burned, distance traveled, and steps taken. MEM 3-axis accelerometer means that it can detect acceleration, inclination and vibration by measuring the motion in the x-, y- and z-axis simultaneously. The device is not waterproof. It's sizes are 35,5mm x 28mm x 9,65 mm and it weights 8 grams. One can access the Fitbit dashboard online[10]. There is also an iPhone application available and various API's to grab the data[11]

Figure 7: FitBit Zip.

11.2 GPS Tracker

The Canmore GT-750(L) Bluetooth, is a lightweight, wireless GPS Logger with Bluetooth® transmission technology and manifold usage possibilities. It can be used with a tablet, smartphone and notebook. The battery lasts up to approx. 13 hours. KML code will be used as a file format to display geographic data in an Earth browser, such as Google Earth, Google Maps, and Google Maps for mobile. KML code is the output of the GPS tracker device[12]. The tracker has a bluetooth interface of operation. The device weights 60 gram (including battery).

[10] http://www.fitbit.com/
[11] http://dev.fitbit.com/
[12] https://developers.google.com/kml/documentation/

Figure 8: GPS tracker.

12. APPENDIX 13 COMMON DESIGN MISTAKES

Underneath a list of the 13 common design mistakes according to Few (2006):

1. Exceeding the boundaries of a single screen;
2. Supplying inadequate context for the data;
3. Displaying excessive detail or precision;
4. Expressing measures indirectly;
5. Choosing inappropriate media of display;
6. Introducing meaningless variety;
7. Using poorly designed display media;
8. Encoding quantitative data inaccurately;
9. Arranging the data poorly;
10. Ineffectively highlighting what's important;
11. Cluttering the screen with useless decoration;
12. Misusing or overusing color;
13. Designing an unappealing visual display.

As well as an overview of an 'ultimate' dashboard.

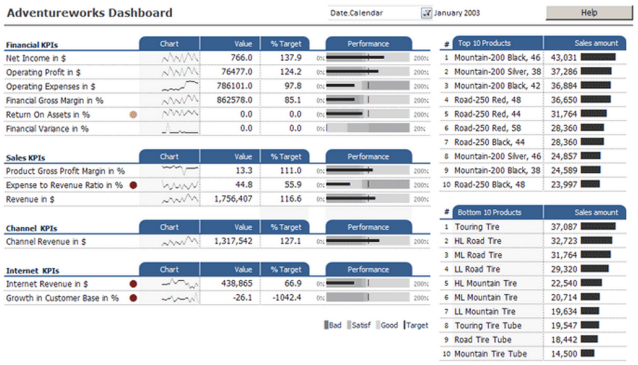

Figure 9: An example of an 'ultimate' dashbaord by Adventureworks 2009.