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Visualization and Visual Analytics

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Abstract—Data surrounds each and every one of us in our daily lives, ranging from exercise logs, to archives of our interactions with others on social media, to online resources pertaining to our hobbies. There is enormous potential for us to use these data to understand ourselves better and make positive changes in our lives. Visualization (Vis) and Visual Analytics (VA) offer substantial opportunities to help individuals gain insights about themselves, their communities and their interests; however, designing tools to support data analysis in non-professional life brings a unique set of research and design challenges. We investigate the requirements and research directions required to take full advantage of Vis and VA in a personal context. We develop a taxonomy of design dimensions to provide a coherent vocabulary for discussing Personal Visualization and Personal Visual Analytics. By identifying and exploring clusters in the design space, we discuss challenges and share perspectives on future research. This work brings together research that was previously scattered across disciplines. Our goal is to call research attention to this space and engage researchers to explore the enabling techniques and technology that will support people to better understand data relevant to their personal lives, interests, and needs.

Index Terms—Taxonomy, personal context, interaction design, mobile and ubiquitous visualization

1 Introduction

WE are surrounded by data in our everyday lives. Many times these data relate to our professional interests, but increasingly we have access to data that has little to do with our work. For instance, we now have access to immense data stores about our communities (e.g., census data). Due to commercial availability of sensors, data describing our health and fitness (e.g., exercise logs, pedometer data) and even our resource usage (e.g., utilities such as water, electricity use) are easily available to us. These data are relevant to our personal lives — they enable us to explore information about ourselves, our communities, and issues that are personally relevant and important to us. Furthermore, existing commercial systems are making visual exploration and reasoning more widely accessible for use in personal situations.

To do this we describe previous and future work as being part of a new field and research community called personal visualization and personal

Personal Visualization (PV) involves the *design of interactive visual data representations for use in a personal context*, and Personal Visual Analytics (PVA) is the *science of analytical reasoning facilitated by visual representations used within a personal context*. The difference between the two areas is analogous to the difference between Vis and VA – Personal Visual Analytics involves both visualization and automatic computer assisted analysis, whereas Personal Visualization focuses on visual data representations. We note that in normal conversation and writing we expect that people will use either PV or PVA, but not both terms together. However, for the purposes of our current review and summary of the areas, in this document we will refer to the two areas collectively as PV&PVA.

The main question that PV&PVA is concerned with is: *How can the power of visualization and visual analytics be made appropriate for use in personal contexts — including for people who have little experience with data, visualization, or statistical reasoning*? There is enormous potential for us to use data to make positive changes in our personal lives and the lives of others, but as visualization and visual analytics experts are well aware, greater availability of data does not on its own lead to new insights. Data must be accessible, understandable, and interpretable before interacting with it can lead to insights or actionable knowledge. Adoption of PV&PVA technologies also depends on how well those technologies fit into people's daily environments and routines.

PV&PVA builds on work in visualization (Vis) and visual analytics (VA) and aims to empower everyday users to develop insights within a *personal context*. Personal context implies non-professional situations, in which people may have quite different motivations, priorities, role expectations, environments, or time and resource budgets as compared to professional situations. Because of these differences, PV&PVA designs necessarily have new requirements and challenges that bring new opportunities for Vis and VA research.

By defining the area of PV&PVA, we hope to provide common ground for research. PV&PVA unites research that is current distributed across visualization, human-computer interaction (HCI), ubiquitous computing, and personal informatics (PI) communities. A successful research agenda for PV&PVA really relies on this unification: PI informs the collection and management of personally relevant data, HCI and ubiquitous computing help us to design effective sensing devices and interactions that fit into people's everyday environments, and visualization helps us understand how to support visual data exploration and analysis activities.

In this paper, we review existing PV&PVA literature across several fields to identify common approaches, findings and gaps. Through our review we establish an initial set of design dimensions to characterize this space and provide a common vocabulary that will make it easier to relate and share information between fields. Our goal is to explore the emerging interest in this field and offer a new perspective on the challenges that arise when designing for personal contexts. We see this work as a new starting point for different fields to learn about one another, thereby unifying a larger community.

In the following sections, we first define the space of PV&PVA (section 2). We then describe our methods and present a taxonomy of design dimensions based on our literature review (section 3). Following this, we summarize recent research trends (Section 4) and use our taxonomy to identify interesting topics that have been explored to date (section 5). Finally, we discuss design challenges and share our perspectives on future research in PV&PVA.

2 Defining The Space of Personal Visualization and Personal Visual Analytics

We have defined Personal Visualization and Personal Visual Analytics in terms of *personal context*: PV&PVA tools are designed for and used within personal contexts. So what exactly is personal context? In activity theory, Nardi [66] argued that context is "both internal, involving specific objects and goals – and, at the same time, external to people, involving artifacts, other people, and specific settings". This concept has been already applied in HCI practice. Internally, context could be "abstract artifacts" [1], such as goals, skill sets, preferences, experience, etc. Externally, context could be either physical constraints (e.g., physical environments or devices) or social influence (e.g., norms in a community or division of labor).

We distinguish personal context from *personal data* (i.e., data about oneself). While PV&PVA applications often involve personal data as well, it is not a requirement of our definition. For example, a person might be interested in exploring census statistics that do not necessarily have personal relevance and are not directly their own data; our definition of PV&PVA is inclusive enough to encompass this type of application.

Our focus on personal context leads to some differences from traditional Vis & VA and some new and interesting research challenges. Most traditional visualization applications

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focus on supporting expert analysts with respect to their occupational roles, which means typical systems (except perhaps those for situational awareness) presume that analysts will have long periods of time to do deep analysis of the data, using workstations with substantial computing power and large screens.

In a personal context, by contrast, people may look into their data with different goals, backgrounds, and expectations (i.e., internal context). While these differences may not exist in every case, our point is that they *very often* exist and are therefore worthy of design and research attention. People may have a lower priority and time budget for performing analytical tasks when they are not part of a work-role expectation, and their motivations may differ from those of people in professional contexts, as discussed by Sprague et al. [76]. The vast majority of people are not visualization or data analytics experts, so analytic tools will need to be accessible. Memories, skills, knowledge, values, and culture impact how people perceive visualizations and interpret data, and this may be particularly true when people perceive the world from a self-centered perspective (i.e., reasoning about things with respect to oneself). In some cases, data may be meaningful only to the individual. External factors that may characterize personal context include devices, use context and social influence. People may use a wide variety of different devices according to the situation, such as mobile devices on the go and ambient displays in their homes. Meanwhile, social influence may impact their behaviors and decisions (e.g., sharing information or experience, setting group goals, or comparing one's performance with peers).

Interactions in a personal context could be different as well. While some people may actively execute deep analytical tasks indistinguishable from most traditional visualization tasks (e.g., Quantified Self or performance training for fitness activities), other tasks could involve passive attention [83] (e.g., ongoing monitoring or ambient awareness facilitated by mobile devices and ambient displays). These passive attention activities need to fit seamlessly into other aspects of people's lives. The point here is not to draw a perfect boundary between PV&PVA and traditional Vis & VA, but rather to highlight a set of new challenges and opportunities that arise when we explicitly consider designing for a personal context.

As PV&PVA research broadens the scope of visualization and visual analytics, it also subsumes many related fields, including casual InfoVis [69], InfoVis for the Masses [21], persuasive computing [30] and personal informatics (PI) [56], [59]. Personal Informatics has become an established research area, and PI tools have been applied to a number of domains, such as health and environmental conservation. However, PI tools and research have largely focused on data collection rather than data presentation and interaction. With their definition of casual infovis, Pousman et al. [69] brought attention to "InfoVis edge cases". However, while their focus was to identify high-level categories of systems that were outside of traditional InfoVis, our focus here is to articulate a taxonomy of design dimensions that characterize PV&PVA.

3 CHALLENGES

Now that we have described the kinds of research that comprise the PV&PVA field, hopefully the reader can see that PV&PVA brings forth a set of new design and research challenges. These new challenges arise because of the unique nature of personal context (e.g., role expectations, environments, and related activities). For example, PV&PVA systems may need to support people with limited visualization literacy and analytics experience, fit into personal life routines and physical surroundings, support fleeting and short term use, support recall of relevant events, and apply appropriate baselines to support reasoning about data. While some of these challenges are not completely new, PV&PVA introduces a unique perspective on these challenges, and emphasizes their importance. In this section, we articulate some of the key challenges that we consider important for advancing the field of PV&PVA. The challenges are a call to action: future research needs to address these issues to enhance PV&PVA tools and expand their impact.

Fit in Personal Routines and Environments

Any tool needs to be designed to fit within its physical environment and context of use. In a personal context, physical environments and activity routines can be quite different from those in professional contexts, leading to new design challenges. For example, we may wish to support fleeting use of a fitness tracking application without interrupting one's life routines, or customize a visualization's appearance so that it matches the aesthetic of a living room where it will be deployed.

Fitting into people's lives means that designers should consider availability, accessibility and ease of use for long-term adoption. Kim identified two stages of how people adopt everyday technologies [49]: in the early stage, interest is the main motivation; then gradually the tool is adopted into daily routines. In a later stage, people's practices with the tool become "rational reasoning rather than from an unconscious and habitual reiteration"; that is, using the tool becomes part of their routines. People's goals are mostly realized in the latter stage; however, the transition to this stage takes time. Furthermore, whether the transition occurs at all depends on how easily the tool fits into the person's life.

There are many barriers that limit the adoption of PV&PVA tools. One way to reduce these barriers is to consider the context of use; for example, designers can reduce the effort required to collect and organize data, so tools can be used with minimal effort or at-a-glance. Visualization designs can be integrated with tools or devices that people use or encounter regularly in their daily routines. Examples include information appliances in the home, ambient wall "art", and mobile devices. For instance, a visualization integrated into mobile phone wallpaper would be frequently encountered as people use their phones.

Recall of Relevant Context for Reasoning

A challenge in PV&PVA is that the appropriate context for interpreting the primary data may not be in the form of data that is easily accessible. Activity theory [1] has recognized that people's understanding and use of information artifacts are strongly influenced by their internal context (experience, preferences, competencies, values, etc.) Relevant internal context for interpreting data in a PV&PVA tool might be the knowledge of one's own past activities, feelings, and interactions with others. From previous experience, a person may be aware that drinking coffee in the evening would cause insomnia [7]. Understanding their temporal patterns of energy use may be difficult without knowing what they were doing at certain times of the day. Some of this necessary context is in the form of memories that are recalled to explain past behaviors. Lee and Dey conducted a study with older people on pill-taking [55]. Participants tended to explain anomalies of pill taking (i.e., forgetting to take pills on time) with "routines and their subtle variations", mostly by digging into their memories. But memory is fallible and imprecise, particularly for older people in this case. Adding additional data from other sources (e.g., with help from context-aware technologies) may help to trigger people's memory and enable them to better make sense of the primary data. We found some encouraging examples in the literature, for example, cultivating actionable knowledge [73] or reminiscing about the past [79].

Overall, relevant context can relate to individual differences, personal experiences, view perspectives, and social encounters. One challenge is that the appropriate context may vary for different people and in different situations. Identifying types of contextual data that will be more generically useful, and devising flexible mechanisms to enable people to recall or recognize contextual data that they consider relevant, may help to enrich the inferential knowledge that people bring when using PV&PVA tools, supporting richer insights.

Defining Appropriate Baselines

Making comparisons is a fundamental way to gain insights from data, and this is equally true for PV&PVA applications. For example, in Baby Steps [45], parents could compare their children's development to milestones provided by a pediatrician. Froehlich et al. [32] used a Metaphorical Unit view (see Fig. 3b), mapping systematic water-consumption units to commonly understandable everyday objects (e.g., jugs or oil trucks). For diabetes control, doctors could recommend the base insulin dosage plan. People could learn about nutrition from a national food guide. In other words, people often need a reference (or baseline) to understand and assess their current situation.

But what baseline should be used for comparison? One challenge is to understand what makes an appropriate comparison set. Should a person's energy usage data be compared to their prior usage levels? Should it be compared to a national average? Should it be compared to their peers' data or data from demographically equivalent people? What does "demographically equivalent" mean? "Appropriate baseline" is an elusive idea, mainly because it depends so heavily on the context of use, goals, and also on each person's values. For instance, many people may be interested in leading healthy lives. Yet, what constitutes "healthy" may differ—for one person, it may be the absence of stress; for another, whether he is sleeping well; for another, her adherence to a national food guide. It is unlikely that we could define a single baseline to satisfy all these goals and values. Moreover, the appropriate baseline is likely to change along with the questions the person is trying to answer. As a possible solution to this challenge, future designs might provide flexibility for a person to choose different baselines depending on their situation and goals or automatically present comparisons with a variety of baselines.

Sharing and Privacy

Sharing experiences and spaces with others (family, friends, social groups, etc.) is an important aspect of everyday life. Already there are many PV&PVA tools with an influence context beyond the self. Examples include tools for sharing memories and experiences among family members or friends [68], [79]. One intriguing space is to apply social interactions to enhance motivation or persuade behavior change, for example, setting group goals [60], comparing your own progress to others' [16], or even interfering with social surveillance [78]. However, this approach should be applied carefully, since social interactions may also evoke negative emotions such as stress or guilt. Moreover, because sharing may enable people to see each other's data (e.g., when using data from peers or theneighborhood as a baseline), privacy must be considered.

For displays of personal data (data about oneself), people may desire even more privacy. We believe that PV&PVA tools will frequently be used by a single viewer, interwoven throughout their day. In some situations we may actually want to have a display that *cannot* be easily interpreted by everyone; it may be important to deliberately design visualizations that are incomprehensible to everyone but the owner. Such designs may be particularly important when personal interest is intrinsic and where privacy may be a concern. In such situations, highly personal-data encodings may be an essential design feature. One example is UbiFit, which provided a view of one's physical activities over the past week on a mobile phone, but did so with an abstract visualization of flowers in a garden. This abstraction aimed to be evocative and personally motivating, and had the benefit of making the data difficult or impossible to read by any other person. This kind of approachis important, since our personal data may be in public view (here on a mobile phone, but perhaps alternatively as an ambient display), and we may want to be selective about to *whom* we reveal the meaning of the display. The possible focus on visualization that is both revealing and insightful to a single viewer and concealing or at least neutral to others is a design approach that has not previously been considered in Vis or VA.

Diversifying Design Perspectives

PV&PVA tools often aim to help people gain insight into their own lives. However, current designs are mostly devised by system designers, who seem to decide "what information to present" and "what metaphor should convey the message" without considering the unique perspectives of individuals. Although many systems in our survey involved users in the design process, nearly all of them were designed by a third party (see Fig. 1). Such designs could be fragile in the face of human and contextual diversity. The disjunction between users and designers may elicit feelings of powerlessness or stress, inhibiting long-term use. We found many comments to this effect in post-study interview results. For example, UpStream
[54] was designed to encourage people to use less water for showering, but the countdown display "induced too much guilt, making showering unnecessarily stressful". BinCam [78], which adopted social surveillance to engage better recycling behaviors, similarly evoked feelings of being "guilty or ashamed." Furthermore, a survey of persuasive technology in sustainability indicated limited evidence for behavior change, particularly over the long-term [10]. Studies have also shown that negative emotions may cause stress and prevent lasting adoption [53].

The question of how much control people can and should have over their data and visualizations remains to be answered. In an inspiring study by Byrne et al., [11], participants were asked to design visualizations, assisted by a custom-designed storytelling application, to tell stories from others' life-logging data. It might be powerful to have a flexible framework that helps people design visualizations for themselves, when they have interest in doing so. Another consideration is the support for group design. Designing visualization tools for peers or groups could engage people in social interactions. For example, constructing one's life history together with family or friends [79] could improve the sharing experience. We consider this a realistic goal: with the right tools, people should be able to customize a visualization enough that they feel that they have designed it themselves. (Even Wordle, a very simple word-cloud visualization, had enough personalization options to allow people to feel "creative" [82].)

Yet another way to diversify design perspectives is to apply variety of design strategies. Returning to the persuasive technologies discussion earlier in this section, recent critiques have argued that persuasive strategies might narrow people's vision, because they are based on the assumption that human behavior can be measured and modeled [10]. What behaviors should change, and in what way, are predetermined by designers, and the systems try to actively encourage behavior change in these directions. An alternative design strategy could be to encourage reflection, enabling people to freely explore historical data and actively link current questions with previous experiences and context. For example, designs could help individuals understand their consumption data to cultivate energy literacy [73]. Reflective and persuasive technologies could be complementary, each providing value in different situations. While persuasive methods may encourage certain in-the-moment decisions, reflective tools may encourage people to actively understand their own behavior and set personally meaningful goals.

Integrating Computer Assisted Analysis

Often in large amounts of data, even with a good visual representation, patterns are not easily recognizable. In addition, some people using PV&PVA tools may spend limited time and effort on analysis of their data. Computer algorithms, on the other hand, are very good at identifying some kinds of patterns in large data sets. Computer assisted pattern recognition could relieve the burden on human attention and reveal interesting insights. Integrating automated analysis approaches with visualization has been at the core of visual analytics research. However, to date, these techniques have been much less prominent in tools designed for a personal context. In our survey, we found only 14 examples of automated analysis in a total of 59 tools. Techniques included clustering or classification [2], [3], [18], [31], [32], [65], layout optimization [2], [24], [75], text analysis [2], [23], [63], dimension reduction [29], and state recognition [70]. Khovanskaya et al. also explored data mining infrastructure for personal informatics [44].

Another promising direction could be to apply data mining and machine learning methods to support exploratory browsing. For example, people could investigate what-if experiments. Before making decisions, people could evaluate the impact of possible solutions [77]. For example, what if I change half of the bulbs into energy efficient ones? What if I change all of them? What if I modify settings of the programmed thermostats? By comparing the possible solutions and their impact, people could have flexibility to make decisions that are affordable or acceptable. Accordingly, in this what-if exploration, interactions would not be limited to visual components. People could also interact with the underlying mathematical models in an intuitive way.

Automated techniques inevitably have design trade-offs. These techniques could simplify the analysis process bymodeling problems with expert knowledge. On the other hand, computer models are likely to have flaws and may not consider all possible factors. For example, ubiGreen [31] could not recognize all physical activities, such as biking. Deep analysis is often a long-term process that involves building a mental model of the data; in these cases, automated techniques should facilitate the process of compiling evidence and producing insights rather than simply generating a conclusion. For example, user input could complement automated data collection [31], the same data could be represented and interpreted with different perspectives [32], or context could be provided to validate computer classification [65].

Evaluation

Evaluation of visualization and VA tools has been an ongoing research discussion for several years. PV&PVA is no exception, and in fact, presents some unique challenges for evaluation. Designers often aim for PV&PVA tools to integrate seamlessly into people's life routines, physical environments, and social situations; these contexts of use would be very difficult to simulate in a controlled lab study. Moreover, we also need to re-consider the metrics that are typically used to assess VA or Vis systems. Time, error, and insights are not the only relevant metrics for evaluating PV&PVA tools, and often may not be the most important ones.

We see *ease* as a conceptual metric that could be used as one basis for evaluating PV&PVA tools. That is, how easily does the tool fit into one's daily life, habits, and routine? Can one "ease" into the use of the tool without effortfully breaking from one's current activities? Can one easily answer the questions they might have of their dataset? Can one easily interpret and understand a visual presentation? Can one easily grow with the tool, moving towards more sophisticated analysis as they gain experience? A flip side of ease is unease: what are the barriers to use that a system imposes [36], [52]? Only a few studies have addressed this adoption issue. In the latest study with Dubuque [26], 40% of the participants reported that they rarely used the system. Obviously, adoption barriers are critical to consider in PV&PVA research.

Note that our concept of *ease* goes far beyond the traditional "ease of use" metric. While ease of use is one relevant aspect, we think of ease much more broadly. Ease can be considered analogous to "comfort". With our concept of ease we can ask whether a tool fits comfortably into people's environments, routines, habits, and social experiences. We can also ask how that comfort level changes as people gain experience with the tool and as their life routines and relationships evolve and adapt over time.

While operationalizing this concept of "ease" is challenging, it should be clear that conventional metrics used to evaluate visualization tools (i.e., task completion time, task errors, and even insights [72]) are not only insufficient, they may be the wrong metrics to use altogether for many scenarios. One unique characteristic of PV&PVA tools is that they may be used to "fill the gaps" in time when one is bored, curious, or doing something else [79]. In contrast, our canonical view of VA tool use is one of a focused information worker actively seeking information or insights. While someone using a PV&PVA tool might be focused on discovering complex insights (e.g., tracking health symptoms), they might be equally likely to use it for purposes such as fun or awareness. Appropriate evaluation methods and metrics for assessing PV&PVA tools are urgently needed to support future research.

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