As Simple As Possible, But No Simpler: Creating Flexibility in Personal Informatics

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Abstract
Personal informatics has become a widespread practice, yet even expert users still face challenges in synthesizing and making sense of data. We suggest that these challenges are related to the complexities introduced once personal context is taken seriously. Through ethnographic research in the Quantified Self community, and an iterative software design process for a project called Data Sense, we offer early indications of what those challenges are, and describe how we approached solving them. We found that users had an easier time of working with data when they could use their own files, when temporal recurrences were surfaced and reminded them of other patterns, and when they could “grab” data directly from visualizations. However, the system did require more user learning than we anticipated.

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Personal informatics; self-tracking; data processing; data literacy.

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H.5.2. User Interfaces: User-Centered Design.

Introduction

The proliferation of inexpensive, reliable sensors in mobile devices has meant that personal informatics has become widespread. Keeping track of wellbeing or health through digital data is no longer limited to the most technologically savvy, those with the strongest medical need, or athletes looking to optimize their performance. In 2010, Li et al. [9] studied the Quantified Self community (QS), a group of self-tracking enthusiasts. They identified key challenges these lead users faced in trying use data. This includes the "collection stage" (e.g., what data to collect, when to enter it, etc.), the "integration stage" (how do you even get it all in one place?) and the "reflection stage" (difficulty visualizing, lack of context to interpret).

Although adoption of sensor technologies is widespread, the challenges identified in this early study have not fully been resolved. Lee et al [8] and Calikli [2] both found that basic usability and data collection issues continued to be a problem in a variety of user groups. Rapp et al [16] see similar issues as a new frontier in quantified self. They note that current uses of self-tracking tools are often surprisingly limited, compared to how much data is being collected. Early abandonment of wearable technologies is a well known, longstanding problem [6, 14]. Here we suggest that as use becomes more long term, the ability to see new aspects of the same data becomes more important, which in turn requires a level of flexibility in how data is shown that we do not see on today's market.

Our Late Breaking Work reports on some initial lessons from the Data Sense project, which sought to address some of the challenges in the "integration stage" and "reflection stage" of making sense of data. While the evidence is still preliminary, we argue that these challenges endure in part because of how personal context informs the ways that dataset are used and interpreted. That is, personal context is indeed person-specific, making it more difficult for designers to be able to safely assume what data means to that person. Removing assumptions about which data is significant to end users adds a host of design challenges, but could support more flexible usages in the long term.

Personal datasets have both a personal context (an individual set of circumstances that determine how a person might interpret data) and a social context (the meanings that particular data streams acquire through use over time [4]). The social context is an important resource that enables designers and end users to take "shortcuts"—that is, make assumptions about what data means. For example, data like 10,000 steps per day, or eating 2000 calories, already have associated meanings, like "being active" or "eating normally." These meanings extend beyond the individual, and have *already* been created through various social and scientific processes. Even if there is not total agreement that eating 2,000 calories a day is "healthy," the cultural associations are in place. Those associations can be used as "shortcuts" to communicate what data is for, and can be highly effective in encouraging or discouraging certain behaviors [3].

However, our previous research in QS [11] has showed that when people assemble their own picture about themselves across multiple data sources, the particular individual circumstances start to matter as much as the scientific meanings and cultural associations in play. For example, one person we interviewed was tracking his mood because he was concerned about a potential mental health problem, and later started tracking sleep out of curiosity. It was only after he saw the data put together that he changed what the sleep data was "for." It was no longer for curiosity, but about whether he could attribute his bad moods to the occasional poor night's sleep or a slip into depression. This use case could not be predicted by the existence of these two datasets alone—it is one of many potential ways to combine and use them, depending on how interest evolves. In this way, not only do designers have to take into account the scientific meaning of data, and the social and cultural valences that come attached, but also the fundamentally unpredictability of what people will see in more complex data. People's goals for using data, and the frames they use to think about what it means, are multiple and evolve over time.

That study also found that users' ability to assert interpretive control—that is, draw their own conclusions—was a valued aspect of whether data became meaningful or useful to that person, or whether it fell flat. While interpretive control is particularly valued in the QS community, other studies have found that interest in exploring one's own data is also widespread. Extensive work in both medical and environmental anthropology shows that "lay" people without statistical or medical backgrounds can and often do take an active role in collecting and interpreting their own data (some key examples include Dumit [5] Murphy [10] and Ottinger [12]). They often have important contextual clues not contained in the data *per se,* something more expert interpreters might not have [17].

This raises a second, related design challenge: how can designers better support data exploration that leaves interpretive control with end users, without presuming that those end users have specialist statistical knowledge? The tools of working with data in its "raw" form are largely designed for use by skilled data scientists. Previous work like Data Wrangler [7] focused on preparing data for use in advanced coding environments, while D3 [1] is used by designers with coding skills. In fact, we found that even among the tech-savvy QS community, it can take self-trackers multiple days to process data into a form that makes sense. Yet once it is "cooked" into a single visualization, such that it can be readily interpreted by someone without specialist knowledge, many alternative explanations or directions are foreclosed. The Body Track project [18] focuses on data exploration for non-technical users, and inspired us to explore additional complementary capabilities.

Methods

Based on the previously mentioned ethnographic research, we built, and continue to iterate on, a research prototype called Data Sense (www.makesenseofdata.com). Data Sense is a web-based tool that provides personal informatics capabilities for self-trackers. The goal is to make it easy and intuitive for self-trackers to use their knowledge of personal context to make sense of their own data. It supports this process through various interactive visualizations, machine-learning technologies, and exchanges with other community members.

Often "clear visualizations" are one-off, fixed visualization where the meaning is fairly obvious. We sought to move away from this model, and support multiple, simultaneous interactive visualizations, so that people can experiment with exploring their data from many points of view. In this way, we do not assume prior knowledge but we do assume an active user who interprets data. We aimed to build an inter*active* not "interpassive" system [19]. Users play an active role in decisions about the most appropriate way to manipulate the data to make it amenable to correlations or other forms of analysis. For example, the user can do this in simple ways, by sub-selecting part of their data along different dimensions (for e.g., time, location, value, etc.).[1] They can also decide whether more sophisticated data processes are appropriate, such as compacting their data using different aggregations (min, max, average, etc. across different dimensions).

We conducted the design and technical exploration in tandem with user research. The user research was primarily ethnographic in nature, and consisted of in-person or remote semi-structured interviews (15 interviews) with current QS community members and self-trackers outside that community. It also involved extensive participant observation in QS events, ongoing interactions with beta-testers (200+), a small survey of beta-testers (n=20) and in-class exercises at graduate-level classes at two universities. Sometimes the user research focused on whether a particular feature was interpreted or used as intended, and at other times it explored users' broader perspectives.

From the implementation point-of-view, we have implemented Data Sense as a modular and extensible framework to support the goal of creating a living research platform. At a high level, the system is composed of many components including a sync service to connect to and get data from supported APIs, database layer, web application, back-end analytics and many libraries that enable the underlying architecture. Our backend is written in Java, while the datastore is MySQL and the frontend uses JavaScript delivering a web application with rich visualizations.

[1] A video example of how this works can be found at www.makesenseofdata.com

Lessons Learned

Based on our early research, we offer the following lessons we learned about handling the peculiarities of individual context, in hopes that other designers facing similar challenges might benefit.

Lesson A. *Support the data that people already use.* With the advent of APIs, much progress has been made with respect to interoperability between data services. We were surprised to learn that the bulk of the data beta testers import onto Data Sense are .csv files, even though we built connectors to twelve popular self-tracking services. Some of these files are downloads from existing services, but many are manually collected spreadsheets of self-reported symptoms, activities, vitamins taken, etc.. This echoes the findings from Pew Research that 69% of Americans keep track of their health, but only 20% of those do so with apps and wearables [13]. This suggests that designers should not assume that all the relevant data will be what other companies or researchers anticipate—some of it will be truly personal. From a technical development perspective, this can be a big challenge because of the variability in file structure for self-tracked files, but it could make data processing systems more responsive to the true concerns of end-users.

Figure 1 Drawing a box over data sub-selects that data, and can become a new dataset for visualizing in other ways.

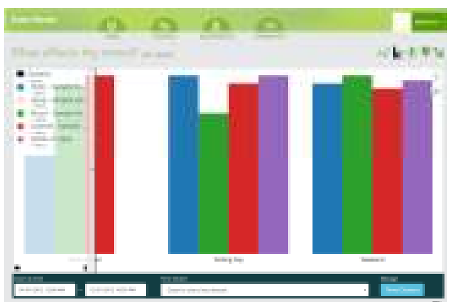

Figure 2 The same data, binned by time in the "periodic pattern" tool. This user has personalized the time bins according to her workweek. The sub-selected data-- "spiked steps"-- falls on her writing day or weekend.

Lesson B. *Time and space surface contextual clues outside the data.* We found that time is an important hinge that allows people to connect patterns in data to patterns in their daily life. The Body Track project offers exploration through zooming in and out, because different patterns can be found at different time scales. We also found that recurring patterns are particularly useful for self-tracking data. For example, one of the authors discovered through the "periodic pattern tool" that she consumed more calories on Mondays and Wednesdays--days her partner taught into the early evening, and they went out rather than cooked. This allowed her to decide whether those specific calories were worthwhile given the context. A user could not spot this on a time series graph, or in a daily calorie "goal." We also provide ways that people can define their own time patterns or what counts as a particular place by drawing directly on a map.

Lesson C. *Visualizations are good places to work directly with data*. In math education, physical objects are often used to teach counting and fractions. Adults also use visualizations in a tactile-like manner [15]. Based on this principle, we have made the visualization of data into the mechanism for sub-selecting data. Instead of "filtering" data, users "grab" data directly off the visualization and move it around on different kinds of plots. For example, instead of providing menus to define a graph to be rendered of all data with values between 100 and 1000, from January to February, users draw a box over a line graph of the full data set corresponding to the relevant X and Y values, and create a new time series to work with (see Figure 1).

In user testing, this feature was shown to be a particularly valued way of doing data cleaning and filtering quickly. For example, one user had not used his steps monitor for some time, and the service had designated those days to be days where zero steps were taken. By selecting only the data that was indeed relevant to his situation—days he knew were not true zeros—other calculations like weekly averages made more sense to him.

Lesson D. As mentioned in the example above on mood and sleep, *data to be contextualized and data to provide the context can shift over time.* For this reason, we designed a feature to create new data streams from existing streams through a set of operators and filters that can be connected and configured in a graphical environment. This enables one dataset to be filtered by another. In this environment, any data can be the context that is used for the filtering, or be the data that is filtered. The previously mentioned user can easily split his mood data into days where he slept well versus poorly, which would allow him to see if there is drop in mood. He could also reverse it, and filter his sleep data by mood if he then decided to look for whether sleep is affected by mood. He could continue to iterate on how much sleep is enough by further configuring these filters, perhaps filtering out periods where other factors were present, and so on. Since these manipulations generate data streams, users can continue to feed these streams for further manipulation on new data as it comes into the service, and visualize it in any of the existing visualizations.

Figure 3: A user filters mood by times when sleep duration was low by dragging the green elements onto a workspace and connecting them.

Lesson E: *New types of abstraction for data analysis still require user learning, even when they meet user needs.* We learned in our early research that to most self-trackers, it makes sense to only look at a small handful of data streams (sleep duration, steps, etc.) at a time. Yet someone who uses just two services-- Fitbit and RescueTime, say--has far more data streams on their hands than makes sense to plot on the same visualization. This forced us to introduce a new concept, the "experiment" in data analysis, as a way to enable users to select a smaller handful data from across their data source that make sense to look at together. Saved "experiments" could then be revisited with updated data. However, new conventions come at the expense of having to provide a more extended system of tutorials and hover-state help than we initially anticipated would be necessary. We found that providing a system that was accessible to non-technical users, in the sense that it did not assume any statistical knowledge, was not the same thing as providing a "simple" system.

While users did find there was a time investment required in getting used to the system, they compared its usability favorably to other data analysis systems out there they have used. Our design choices could be improved upon, of course, but the process made clear that unfamiliar conventions will be necessary, and it take time before users would consider them intuitive. This is a well known issue in hardware innovation—the mouse famously failed early usability testing—but is perhaps less fully understood with respect to data.

Future Directions

Currently, we are adding inference capabilities and data sharing capabilities, where users can exchange results, methods and access to data with each other in an opt-in basis, to further contextualize their own data. These features are a response to how we saw self-trackers learning from each other, creating visualizations not just for themselves, but to teach and learn from others. This effort fits in to the ongoing discussion within the Quantified Self community concerning how self-tracking data might inform public health knowledge. Specifically, there are concerns in that community that public participation in public health is severely limited if the public can only ever donate data to professional research efforts, and is not also given the opportunity to shape the research questions that get asked. The ability to work with one's own data in an open-ended way is, in a sense, a way for self-trackers to arrive at their own research questions, even if the "study" in question is an uncontrolled n of 1. The question then becomes, given the idiosyncratic circumstances in which this data was created and explored, what aspects of it also matter to others?

The adoption of self-tracking devices is now well established, but our experience suggests that personal informatics as a synthesizing process of personal meaning-making is still relatively nascent. While Data Sense has limitations, the prototyping process has revealed wider design challenges of building for the personal, idiosyncratic nature of self-tracking data.

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