Design and data

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Design and Data: Strategies for Designing Information Products in Team Settings

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This chapter aims at linking data and information to creative design, focusing on collaborative processes at early phases of the design with data. The chapter aims at providing clarity in a large space around design and data. Thus, it serves as a guide for design team's approach towards the challenges of data design. Consequently, design is one of the key disciplines involved in data and information visualization (Moere and Purchase, 2011). This chapter starts with a short introduction of ideas and concepts in the intersection of data, information, and design. It looks at users and designers as the main stakeholders, and considered the purpose of designed information. Following this introduction, we first focus on design artifacts essential for collaborative data design practices. Secondly, we focus on what it means to integrate data with design and the potential roles of data in the data design process. The chapter outlines a general design process with methods and approaches towards early design challenges. Furthermore, this chapter concludes with an annotated bibliography to guide further reading. Along the chapter runs an example case of a real information product that helps for better understanding. It links the more theoretical elaborations to the application level of a concrete design case.

Introduction

Design often means to trust intuition and our senses about aesthetics, look and feel, or the emotions that our products stimulate. Design opportunities are sought especially at the early phases of designing. Thus, we might not only rely both on user research and ethnography, but also on intuition to find an issue to design for.

Consequently, what we need to achieve with design is (1) to effectively translate gathered, sensed, or observed data into information without losing important qualities such as meaning, connections, truthfulness; (2) to achieve a balance between complexity, understandability, and ease of use by means of interaction; and (3) to allow a design process guided by a few core principles that reliably leads towards good designs.

With the data involved, the game changes (Bigelow et al., 2014). Thus, data is very special in the sense that it may appear as an ingredient of a design process. It may also be the subject of design, which is the primary focus of this chapter: in-

formation products such as interactive data visualizations, wearable health trackers, and mobile apps communicating data about everyday life. In times of ubiquitous “big data” with even more invading collection practices, we need to find ways to turn raw data into meaningful designs: “information products”. Apart from that, designing with data is in itself a complex field. Hence, there are three main challenges addressed in this chapter:

1. **Modality and Materiality of Data:** Data is inherently intangible and ephemeral. It cannot be changed and modified. It expires easily, but can remain useful.
2. **Meaning and Meta-data:** Data gets meaning by contextualization, linking, and relating. These are the outcomes of processing and annotation.
3. **Scope and Framing:** Data available for design can be overwhelming in terms of quantity and quality. Nowadays especially, scoping and framing can be real problems in a data design.

In addressing these three challenges, the chapter provides guidance with clear-cut design artifacts and process phases. In this chapter, we will focus on *information products*, i.e., packaged design artifacts that represent and embed data into the context of the end-user. Thus, two main stakeholders are relevant in this context: the end-user and the designer in a team of potentially more technical or entrepreneurial stakeholders. We will focus on information products that reflect data and information meaningfully, and highlight the influence of data for the design team.

Fig. 1. Qualica physical information product used in two different contexts: sport and work

Example Case

As a general illustration for this chapter, an example case runs along the sections, and will develop with the chapter. After every section, the section context will be related to and explained with the design case: a personal wearable device visualizing different layers of (activity) data in a minimal way depends on the context the user is currently in. This is because our needs for information greatly differ with the context. For instance, when exercising, we are interested in the heart

rate. However, when working, we might be more interested in nudges to relieve stress or that pushes us to take a break. This concept, *Qualica*, was designed for users in a changing world, in which visual media and communication activities increasingly dominate their reality and do so in a noisy way. Therefore, this concept leverages minimal visualization in context, instead of showing numbers, charts, or iconic visualizations.

Essentially, this is an information product combining data, contextual information with real-time data processing, interaction, and a minimal visualization in wearable design (see Figure 1 for *Qualica* in different contexts). To better illustrate the design process, we assume that different roles are involved in the early design phases of this case. This separates the different concerns such as: a technical expert on bio-signal data and external APIs; an industrial designer who will not only design the device's form and interaction, but also the service around this; and a mobile application developer responsible for the development of the *Qualica* companion app. In the development of the chapter, we will see how the case evolves. The concept was taken from Pepijn Fens' Master thesis, including all illustrations relating to the example case (Fens, 2014).

In the following section, data is introduced as material for design, and as material that potentially carries meaning. However, it is also challenging to design with, especially in team settings. The section introduces information products and elaborates on how different usage scenarios of information products influence the design (exploration and communication). The next section focuses on artifacts involved in the data design process, with special attention to separation of concerns and design information. Thus, this was before leading into a section detailing a design process that draws relations between artifacts and different phases of the design process.

From Data to Information Products

Data for design? What is¹ this strange ingredient that is found everywhere today, but hard to grasp and often harder to understand? Unlike other “materials”, data is an abstract, dynamic, and less malleable resource which needs special attention. Data can be seen as granulate of meaning in space and time.

Throughout the design process, the needs for data and information change from exploration to clearer communication. In the later stages, the designer knows what to expect from the data and information sources. He has become familiar with the data, and has found something interesting and worthwhile for further designing.

¹ In this chapter, the word “data” is used mainly in the singular form. For discussion: see Borgman (2015).

Thus, this aspect of the data now needs to be nurtured and emphasized for the final design of the information product.

Data as Material

The reality that surrounds us is increasingly captured in the form of data. Therefore, data has become an explicit resource that is known and potentially feared by the public. But what is this again?

According to Ackoff (1989), data, information, knowledge, and wisdom are linked in a hierarchical way. With data as the base layer, information can be derived. Furthermore, we derive knowledge from information when processing it, and potentially turn our knowledge to wisdom at some point. However, this view that suggests that data is the basis and also the most resourceful of the four was challenged (Tuomi 1999). Data is simply a form of information that is *optimized for machines* and that can appear in raw or processed forms. Data can be often empirical, that is, collected in a formal experiment or study, or coming from the field as field data. Raw data is often considered rich and truthful, but unusable for higher-level design activities. Thus, the central point is that data is an abstract concept and is often derived from the real world. Some authors have even suggested *capta* to be a more accurate description of what is commonly called data i.e., a likely biased interpretation of reality (Drucker, 2011). Naturally, there are many views on data and information. Therefore, we will use the following interpretation in the remainder: data is processed by machines; information is processed by humans; and “information causes change. If it does not, it is not information.” (Claude Shannon).

Material Meaning

The interesting future is not about data at all, it is about meaning.

Alan Kay

The challenge in designing with data is clearly in conveying meaning, to translate from the abstract to the semantically expression that touches us and that brings about a change. When designing with data as a material, we need to think about what is the meaning of data in the design process and how much we need to deal with it. At the same time, what would be the meaning for users? Would they need an explorative design, meant to extend the knowledge of a domain, a design subject, or simply reality? Would they need data presented for action, to inform, to influence, to engage, and to trigger? Consequently, designers are in charge of adding meaning to the material data. This is often in the form of contextual information, relational linking, or simply by explaining what is captured in the dataset.

They need to consider the fact that transparency and honesty are related. Transparency links to the degree of access to the original dataset or data sources, whereas honesty links to the question on how a reduced image of the original can still truthfully convey a gist of what has been captured originally (Hullman and Diakopoulos, 2011). In most data design projects, there comes the point when the original view of the raw data is lost. As a result, certain information takes its place, when a view more colored by the makers' influence is finally presented to the users. As we will see, it is advisable to step back from time to time and to think about why we need to introduce a certain piece of data into design. In addition, we also consider *why* the user needs to know something: are we solving a problem or are we exploring a (potential) dataset that might solve future problems directly or indirectly?

Information Products

Information products are ubiquitous nowadays, but seldom defined or seen as such: *information products are end-user products that package information in a user-friendly manner, can communicate easily, and possibly have a rich (interactive) experience*. Increasingly, we are able to capture these aspects from devices in the field, and the services connected to them. In the past, computers were not able to access more information than they would actually need to carry out their assigned tasks. With the introduction of smart phones and other smart devices, we learned to accept that embedded sensors capture more data than is actually needed. Thus, we arrived at the conclusion that every new sensor creates a new business opportunity, with design at the core of it. Increasingly, this means that we are also able to act upon ad-hoc collected data with our products.

Design for Exploration

End-user scenarios for information products are often leaning more towards communication than exploration. However, there are also explorative scenarios for end-users. One example are the map-based visualizations of radiation data (appearing after the Fukushima accident in March 2011²), which is fairly close to the raw data in real-time, simply extended or contextualized with spatial information. Still, a strong message can be understood by data explorers around the world. Explorative information products are useful when users (consumers and professionals) need to access a vast amount of potentially diverse information through a comparatively limited interface. According to Heer and Shneiderman (2012), Common techniques adopted by designers include:

² <http://blog.safecast.org/maps/>; last accessed: Dec 31, 2014

³ http://en.wikipedia.org/wiki/Discrete-time_signal, last accessed Dec 31, 2014

- Selection (for example, retrieving hidden contextual information of a precise point in time or location).
- Filtering (reducing the shown data by time or location; excluding or including data items).
- Zooming (decreasing the amount of space in view, increasing data points per location, and changing the level of abstraction).
- Navigation or browsing (showing a directory of available categories or search terms).
- Augmentation (dynamic linking of data items to external information or meta-data).

The shared expectation of such an explorative design is that due to the increased complexity, other benefits can be gained. Such benefits include: truthfulness and less potential bias, flexibility in how data can be viewed, and generally better insight into complex relationships between data items and between the data set and external information. An explorative view can mean also that meta-data and sources are disclosed and available in the user's interface. Consequently, this can provide another layer of information on how the data at hand was gathered, processed, and manipulated. Hence, it provides a lens to frame, understand, and interpret the data.

Design for Communication and Influence

What if data was used less in a explorative way, and more *to communicate and inspire action*? Good examples are personal health and activity tracking devices (Fens and Funk, 2014), data visualizations in the public media, and other designs that access a data from a data source and translate it into a contextually enriched and visually lifted representation that appeals to the senses of the viewers. Such data designs focus often on the viewer. For various reasons, it excludes data about other users. Furthermore, an explorative view would include this, which leads to the idea that communicative designs can address a larger audience. This is possible because they disclose less potentially privacy-relevant information. Instead, they give an emphasis on collective and viewer-related aspects of data.

A central question is how can data lead whom to what action. This question introduces the notion of *actionable* knowledge. Actionable knowledge is a knowledge that is not tacit or bound to be forgotten soon, but is *useful*, and often leads to direct action. At the same time, the question extends towards persuasive designs that include a superficially reputable motivation or argumentation i.e., data from a credible source. Many applications of such a pattern however lacks credibility, as the chain from data collection to representation is broken and blurry in many places.

Example Case

Looking at the example case of an information *product*, the design is less explorative and more communicative. Therefore, the data that is sensed or drawn from external data sources, such as activity streams on the Internet, is not disclosed in full, but instead presented in an aggregated and highly condensed way through a simple physical display. This display is a multi-color LED bar encased in the wearable device as a casual accessory. While this can potentially lead to an explorative behavior on the user's side, the primary use case is informative, suggestive, and inspires behavioral change (towards the more healthy and aware).

Fig. 2. Qualica companion app, covering a more explorative usage scenario on personal health

There is also a companion app that links to the wearable device and allows for browsing collected data, exploring historical traces, or zooming into the specifics of a context. Several screens of this app are shown in Figure 2. This gives the user a better understanding of the richness of the multi-layered data basis used in the Qualica design. When Qualica relates bodily activity to work statistics such as desktop application usage, the user might feel triggered to look into such a pattern. This app and its more explorative use scenario is not the focus of the remaining part of this chapter. It can be seen from Fens (2014).

After the introduction of information products, the following section focuses on the creation (process) of such products, starting with the artifacts of the data design process.

Artifacts for Designing with Data

The view that was presented in the previous section which places data in a pyramid with wisdom at the top, might work for a general reception of data and information from a user or consumer point of view. Nevertheless, this will not work for the data designer who might not be working alone. Therefore, a different understanding of data and information is necessary. We need to separate the design and underlying information to allow for collaboration between different data stakeholders and to support ideation in the early phases with a neutral representation of available information. Therefore, this is flexible enough for rapid prototyping and fast iterative cycles at the same time. This information in turn needs to be described in a way that clearly separates data sources and processing from the data workbench that the designer finally spends most time on. Finally, separation of concerns is a way to split a potentially monolithic entity into smaller parts that can be taken over by different experts in a collaborative setting.

These considerations lead to a new understanding of data and information in the context of design as a layered schema that stacks design infrastructure, design information, and the design vertically (cf. Figure 3). What sounds rather technical and maybe even seem to be (over-)applying engineering principles to a design process, is an important forcing function. Architect Christopher Alexander (Alexander 1964) noted earlier on how successful designs need to unfold and be the outcomes of experimentation, iteration, mistakes, and failures. Design information is the breeding ground for such a process of repeated adaptations and “weathering” of a data design. Design information is a safe middle ground which helps to explore and iterate fast. Also, it constrains attempts to lose direction, momentum, and drive.

Fig. 3. Schematic overview of data design layers and possible experts

As shown in the figure on the left side, the *design infrastructure* encapsulates the means to acquire and process data and provides an interface to the data. *Design information* is the translation of what the infrastructure delivers into a view or representation that can be used during the design process as a full-fledged reference for what the data is. The *design*, finally, is the finished *packaging* of the data that allows for limited, but meaningful interactions with the underlying data sources.

On the right side of the figure, a few expert roles were depicted (by all means are not exhaustive), which could work together in a collaborative design team. While all experts would be involved at all levels to some degree, the role next to the block shows their main expertise and responsibility. The figure shows clearly the need for good communication means between different professions and backgrounds. The described division into layers of design artifacts can facilitate this and shall be explained in detail in the following.

Data Infrastructure, from Source and Raw Data to Processed Data

Designing with data inherently means to gather, collect, and prepare the material of design, data, and related information, in a way that it is suited for the remainder of the design process. This is hard. Data material is different in that its collection often decides on its value. The amount can be important, the method of collecting contributes to its validity, and the analysis of data needs to be con-

sistent, following a clear approach even at the very beginning. At the same time, the semantics and meaning of data, and their combination with other information and other factors, determines the value of data and its degree of degradation. Depending on its later use, data can lose or gain value over time. As an example, data that links to a competitive advantage loses its value quickly (cf. high-frequency stock trading or leaked secret cookie recipes). Nevertheless, if used as an evidence, suddenly it has a lot of value (cf. prior art for patents or evidence in a court trial). Treating data right involves a lot of intuitive aspects, which often leads to the pitfall of misunderstanding that “interesting” does not always equal to “valuable”.

Data Sources and Data Collection

Regardless of whether the design finally incorporates a particular data set or not, data sources are essentially touch points with the users’ reality. Data can be extracted from this reality by measuring or observing, for example, by applying technology to measure data from the environment (temperature, radiation, noise-level etc.) or by using human observation and interpretation of reality. These general approaches deliver different types of data. Therefore, they can be applied separately or together, as it is needed. Sometimes, it is more efficient or accurate to utilize technology for measurement. Sometimes also, the human mind is crucial to observe, report or interpret the desired data.

To frame the general challenge of data sources for more technical design: what is it that we can measure through products about users, their environment, their experience, and also their intentions, needs, and expectations? Increasingly, we are able to capture these aspects from devices in the field, and the services connected to them. Furthermore, two main areas of data attract the interest of designers: (1) data about humans, users, and their environment; and (2) data about the products they use and experience. Thus, we will focus on these two areas. The first one is interesting for designing *information products*, while the second one approaches data as a means to get better *insight* into a product’s (potential) users and to adapt and tailor the design.

Consequently, there are many ways through which data can lose its value due to processing, and also due to the simple fact that reality can seldom be fully represented in data. We can generalize these aspects towards general quality criteria for data that should be useful for design. These criteria include:

- *Availability*: Data sources need to be available not only in the moment when data is captured, but also later on. This is required for reference or simply for updating a previously collected dataset. Readily available data is essential for an iterative design process and for establishing support infrastructure and design information.

- *Relevance*: Data sources need to be credible, valid, and honest for anything derived from them to be considered relevant and meaningful. Relevance over time is important in the sense that data can become easily outdated or “cold”, resulting in less relevance for some applications.
- *Context*: Data sources belong to a particular context, which needs to be captured in some way for later reference and information enrichment. Thus, only with sufficient contextual information, a dataset can “land”. Data that is deprived of its context becomes more abstract, and some contextual information needs to be added to re-create meaning.
- *Accuracy*: Accuracy is combination of trueness and precision (according to ISO 5725-1) (Feinberg, 1995). Trueness refers to how far the measurement or data point is from the ground truth, whereas precision essentially determines the distribution of samples. Low accuracy can result from close data points (high precision), and distance from the ground truth (trueness), and vice versa. Due to limitations in technology and storage, data is *sampled*, that means snapshots are taken (see Figure 4). Thus, this automatically introduces lower accuracy.
- *Privacy*: Data can indeed invade a person’s privacy, revealing or showing the potential to reveal personal and intimate information. Privacy problems are actually problems of contextualizing data, e.g. a person’s identifiable details. As an example, without any context, “102,000” surely did not touch anyone’s privacy. Nevertheless, it does only if it is brought together with the context “2013 taxable income in EUR of Joe Doe, living in ...”. Context, true or false, can create a certain rooting in reality that lends great power to data. Privacy deserves special attention in the designing of data. Approaches to deal with privacy-sensitive information involve maintaining de-contextualization consistently. Such approaches need to be tight, and the intuitive nature of dealing with data does not allow for even simple mistakes.

When talking about qualities, one assumes that such aspects should be maximized. This is not necessarily so. When designing with data, qualities call for balance and not for full maximization. Two examples: People do value privacy; and they are willing to compromise if they receive benefits to give-up privacy partly. Facebook and other social networks demonstrate this: users voluntarily reveal their private, personal, and even intimate information in exchange for social interaction, visibility, and perceived status. Another example is the accuracy of presented information. Modern sensors deliver extremely precise data that signal-processing applications can greatly benefit from. However, in contemporary data visualizations, one can observe that much less precise information is given. This is simply because it is not needed or is even considered harmful and distracting.

In addition, there are more aspects of data such as ownership, storage, security, and governance, which are relevant in differing degrees to enterprise data, “quan-

tified self” data, and environmental data. However, these are beyond the scope of this chapter.

Fig. 4. Example of transferring a continuous (analog) signal into a discrete (digital) representation results in information loss in two dimensions: snapshots are taken in time (left side, horizontal raster) and values of these snapshots are quantized (right side, vertical raster)³.

How to collect data from such data sources is more of a technical matter, but largely depends on the area of data in the design that we are interested in. It is advisable to identify and develop data sources that can deliver data steadily and with little effort. However, this is because “freshness” often determines relevance and meaning in this design space.

Sometimes, such fresh data which is generated continuously is called “online” data, and it often emphasizes its *connected* nature. However, “online” as a concept leads to “offline” data, which is about to leave a relevant time context and become *stale*. Both online and offline data can pose (technical) challenges. For instance, online data needs connectivity, real-time processing, and frequent updating of visual representations which need to be designed specifically for changing data. Offline data needs to be stored, might be more plentiful, and needs potentially stronger contextual enrichment as it lacks timeliness.

Often, it is beneficial if we can influence (online) data collection in terms of selection of sources, granularity, and semantics. Furthermore, changes in the data acquisition process lead to changes in the dataset and we might need to wait until we can process this new data.

Analyzing and Processing Data

Raw data, online or offline, to processed information is often a long winding road. Experts are needed to guide and facilitate understanding of what data source actually can reveal about our experienced reality. However, when analyzing data, different movements can be observed:

³ http://en.wikipedia.org/wiki/Discrete-time_signal, last accessed Dec 31, 2014

- *Down*: Trying to understand the rooting of data in reality, where it comes from, and what it means.
- *Up*: Trying to understand how abstraction can help generalize or connect to common knowledge and interaction.
- *Side-ways across the Dataset*: Trying to understand patterns and links between data items of the same source or reality (phenomenon).
- *Side-ways beyond the Dataset*: Trying to understand how data relates to other information beyond the dataset.

These movements are connected to skeptical analysis of what is there. Also, they help question our perception from time to time. A good example of a fallacy that might bias the analysis of a dataset is *Simpson's paradox*. Simpson's paradox is essentially a paradox about how aggregate statistics can mislead us. A pattern that can be found in distinct parts of the dataset does not appear when all data are combined together. For common sense protests, statistics knows it better (Blyth, 1972).

All steps in a data processing chain determine its later value. Looking at the *collaborative* nature of early design processes, data collection and analysis starts as a manual effort and with the serious involvement of experts in sensors, APIs, signal processing, and data analysis. It is, however, desirable that this flow from raw data towards processed information should be highly automated for later stages of the design process (see the next main section). Thus, there is almost a direct link between the sources of data and the interfaces provided on the surface of the design infrastructure. If the sources of data are multiple users' subjective answers and are the sentiments of other qualitative contributions, it might be advisable to either work with automatically generated "mock" data or to begin with a larger body of historical data.

Fig. 5. Processed bodily activity data in a 3D plot. This visual overview of heart rate, galvanic skin response (GSR), and skin temperature is useful for looking at the “big picture” for spotting patterns, trends and correlations.

Automation is the key, but not for the price of architectural rigidity. What a designer wants is fluency and up-to-date data. Furthermore, the designer also considers the flexibility to change the data sources, to change the way the data is processed, and to interact directly with the data sources if needed. However, processing requires data. Thus, for an existing static dataset, this is easier. For dynamic data, especially in cases where the data is not captured yet, it is a bit more difficult. Furthermore, there is a distinction between offline and online data collection. Offline data is captured and will remain same regardless of what analysis that is needed from the data set.

Interfaces to Data

In the last step towards *design information*, processed information which is still in the engineering realm needs to be made accessible to designers. This can happen in files and folders for bounded datasets, or it can happen in technical interfaces that are potentially even online and continuously accessible, i.e., they deliver fresh data at any point in time. These interfaces are commonly called application programming interfaces (APIs). They are specifications of what an external party can provide or receive from the application. The external party might need to provide credentials to be authorized, but after this step, the door is open for data retrieval.

For data, such an interface is relatively common in the domain of web information systems. Nowadays, Internet giants open up their immense data stores towards developers who can make use of their knowledge and services. This has benefits for developers, but also costs. Especially when not paying for services or access, the developer locks herself into a specific eco-system of the API provider. Therefore, leaving the warm nest might not be so easy after a while.

Still, it is interesting to understand how large companies open their data caches. Certainly, the information is pre-processed and carefully “designed” to fit multiple use case scenarios. Exactly, this eco-system enables what we now know as the startup economy, a network of fast and highly versatile companies developed based on common technologies and information. Furthermore, we can translate this into the smaller context of a data design project. This is done by building interfaces to processed information from the desired data sources delivered on demand. At the same time, we can create a fertile environment for rapid prototyping and experimentation.

What is needed? Data needs to be opened, structured, consistent, and contextualized. Formats matter includes comma-separated value (CSV) files, spreadsheets (for instance, in Microsoft Excel format), databases (MySQL, SQLite, etc. together with their management interfaces), or specialized APIs to remote servers that provide information in readily consumable formats directly queried from internal databases.

These interfaces need not just to be there, they also need to be well documented. Source code, wikis, examples, tutorials, templates, and more formal code or API documentation help designers to create their main data design artifacts, i.e., *design information*.

Example Case

Looking at the example case, there are a number of *data sources* at different layers that contribute to the body of online and offline data that is visualized and communicated to the end-users. They include: bodily signals (cf. Figure 5), work related log data (e.g., use of desktop applications), environmental information (weather, climate etc.), social data from social networks, and data about the current activity context (e.g., running, working, eating etc.). Some of these data sources are accessed actively at frequent moments, and their information is relevant for the current state of the visualization. Therefore, they are classified as “online”. In Figure 6, these online data sources can be gradually found at the bottom. There are also “offline” data sources that are queried less frequently and that do not contribute in real-time to the state of the visualization. Thus, their data is more stable and less volatile, and it provides a more general picture of the context and activity.

The data coming from these sources would be processed, for instance, to normalize the time or number format. For some data sources like weather or social activity streams, online data is available via APIs on the Internet. These data sources would need extra infrastructure to be accessible for the later stages. For wearable devices, data extraction can be difficult or at least cumbersome. At least, samples of relevant data needs to be taken and made available through the data infrastructure. The goal is to have all data programmatically accessible through various channels and to be available as “fresh” as possible.

Fig. 6. Layered approach to visualizing complementary data sources and contextual information

Design Information

One of the designer’s qualities is immediacy with material. To develop this for data, it means not just deeply understanding where data is originating from and what context it belongs to, but being able to work intuitively with specific data and information. Often times, the designer leans into craftsmanship (Megens et al., 2013). And, over time, we might even develop “data smell”, which is an intuitive capability to sense the most interesting aspects of a dataset. As a (partial) craftsman, how many define a designer? Nowadays, building and shaping your own set of tools is an essential skill that can even precede the true expression of your craft.

Nevertheless, as a beginner in designing with data, it is tempting to pursue design directly from data sources or processed data. In addition, we might envision the final form already and are eager to proceed. Climbing Mt. Everest in one day could be successful, but who would take the chances? Instead, a base camp is installed at a location from which the final attempts can be ventured. Thus, this is also convenient to retract to, in case of unforeseen events. The same is true for the attempt to design with data. The designer needs a base camp that allows for exploration, but always provides a good representation of the data at hand, with rough, but versatile visualizations and means to drill down. The designer also needs support to go back and fact-check their work, and to re-evaluate or calculate aggre-

gates. Design information together with a documented approach helps in leaving breadcrumbs that let us backtrack from a cul-de-sac.

Another aspect is the communication between different stakeholders during the collaborative data design process. Thus, design information is an artifact that facilitates common ground among the team members and is the basis for creative decision processes (Kozlova, 2011).

Coming back to the idea of offline and online data, the former is good to have a broad overview in relating time and space. Also, it enables the search for patterns and hidden links within the dataset. Such design information can be captured in tools, such as the commercial Microsoft Excel spreadsheet tool or specialized tools like Tableau, RAW, or even Matlab. The choice of tools depends on our familiarity with them, and on the degrees of freedom we need to fully understand dynamic data and to reveal the most interesting aspects of it with ease and fluidity. Consequently, several good visual overviews of tools can be found on the Internet⁴.

For *online* data, immediacy is often more interesting. What happens when certain values of different sensors comes in? What are the extreme cases? How can other information enrich the perspective of the given data? In these cases, design information might be a handcrafted visualization that fits our personal needs and which has grown over time. Many developers and designers have in the past ventured into tool making and maintain a personal set of helpers, resources, and craft support tools which allow them to work fast and intuitively. The goal is to establish this for data as well.

Behavioral Data for Design

As with almost every design process at the beginning, there is always a question asked: whom are we designing for and what are their needs and expectations? There are differences between nonprofessional and professional users in dealing with data visualizations (Quispel and Maes, 2014). However, even the *makers* of visualizations are an interesting group to be taken into account in the context of design and data. While the above questions can help designers frame their product ideas, the inherent natural tendency towards an idealized persona can also be misleading. There is another way: data about the user's intentions, needs, expectations, and also behavior can help form a more empirical view of who we are designing for, what are the needs they have, and how people might anticipate future designs (Sprague and Tory, 2012; Brehmer et al., 2014). This is an explorative use of gathered data that over time provides an incrementally more accurate view on the users of a design.

⁴ One example: <http://keshif.me/demo/VisTools>; last accessed on Sept 5, 2015

Such data supporting the design process in exploration, design, and also in validation, requires appropriate data sources that will elicit properly contextualized data about the behavior of users within the target group and potentially their needs and expectations. The former data can be derived nowadays from the instrumentation of early prototypes, and later, products, whereas the latter information can be observed or derived from questionnaires, interviews, and other qualitative user's research methods. The combination of such different kinds of data leads to data design tools that optimally support the now data-driven design process (Funk, 2011).

Subsequently, this is related to other data-driven design approaches such as evidence-based design in the healthcare domain (Evans, 2010; Codinhoto, 2013) and statistical hypothesis testing such as “A/B testing”. Furthermore, it also involves the more general split testing approaches (Fogg et al., 2001; Kohavi et al., 2009), which are however out of the scope of this chapter.

Fig. 7. Design information for Qualica, a rough data visualization providing versatile access to the processed data interactive control for selection, filtering, brushing and annotation

Example Case

Looking again at the example case, design information is necessary to make better decisions in a design space filled with sensible options and a wealth of different data sources available through the data interface. The interface shown in Figure 7 was developed to give an overview of all body related data sources. Thus, it allows for easy browsing and selection, and also for comparing and annotating points in time with contextual information that would be helpful in later stages of the design process. This interface could be used from the data perspective (towards the context given by annotations) and vice versa, and from annotations to the underlying “hard data”. Based on the platform of the design information, different directions for the user interface design can be explored. For instance, a more communicative and information-limited product concept next to an explorative variant targeting different kinds of end-users, can be explored.

Generalization of Design Information into Design Tools

Design information is an encapsulation of data or information enriched by contextual information, which is tailored towards a clear user’s base. When we turn from the end-users of the designed products to the designers and makers as users, the data is certainly useful in the design process for ideation, conceptualization, designing, and also validating a design. While design information and its user interface can be very specific to a design project, it can also be generalized towards a reusable data “workbench” with easily accessible processing steps, data manipulation tools, and visualizations. Examples are interactive complex data visualizations such as process graphs and mapped data. Others include information services, professional dashboards, and other analytical business tools, i.e., domain-specific tools.

There is a tradition in crafts which states that craftsmen often need to create non-existent tools or adapt tools to their own practice or special use-cases. With data, designers need to embrace this thought as well. However, this thought shows that data is complex and highly context-sensitive, which requires deep understanding and customized tools that can deal with such matter appropriately.

Design Product

Consequently, the *design product* that results from an elaborate design process is less, and at the same time, more than the design information. It is *less* in the sense that the final design usually reduces and condenses the given design information towards a clean and polished (visual) representation of the data that optimizes understandability, experience, and ease of use. It is *more* in the sense that the design contextualizes and roots the information in the user’s and not the designer’s reality. Semantic hints are taken into account in the presentation, and dynamic visual

or physical presentations can adapt to the context of use. The designer might, for instance, use storytelling (Kosara and Mackinlay, 2013) as a means to introduce the scope of the design, align the presented information with the reality of the users (Chuah and Roth, 2003), and capture their attention and thoughts using a strong narrative.

Therefore, the designer capitalizes on the richness of the design information to optimize the design, and to iterate in cycles between the three layers as we will see in the next section.

Design Process

As we now know how to distinguish between the technical realm, *design infrastructure*, and the design space, the *design information* and the *design* itself, we turn towards the second view of the creation of information products. This view involves the actual process of designing with data. Two key points need attention. Firstly, having a layer of design information is essential for collaboration support, communication, fast progress, and stabilizing the design process at a later point. However, this needs to be established *fast*. Secondly, investing too much engineering efforts in an infrastructure or platform prematurely should be avoided because it will definitely change anyhow. Following this process is certainly a variant of an old engineering issue: achieving a good balance between generalization and structure, and flexibility and adaptability by improving a system without introducing too much technical debt⁵.

Fig. 8. Data design process with different layers of data in three phases: bootstrapping, exploration, and design iterations.

Consequently, the different phases of the data design process (as depicted in Figure 8) will be explained in detail, starting with the bootstrapping phase.

⁵ <http://c2.com/cgi/wiki/TechnicalDebt>, last accessed Dec 31, 2014.

Bootstrapping

Bootstrapping the design process can be as simple as assembling all people involved, sketching the challenge or brief, and getting a feeling for the different disciplines involved. A recommendation is prepared by letting everyone summarize their view on the project (why is the project relevant, interesting, and worthwhile?), their expertise (what brought them to the table?), and their input. Furthermore, everyone should be able to quickly grasp the challenges of the involved data. At the other end of the spectrum, they should consider what a potential design should look like. On the data side, it is important to understand some initial aspects about the data such as: what data sources are available, how are the data generated and structured, which technology contains the data, and which tools could be of use for its analysis? And then again, what are our assumptions about the data? Are they factually accurate, potentially biased, or over-simplistic? It is important to be skeptical even if we do not consider all these questions as relevant, maybe our audience does?

In the process overview (cf. Figure 8), the bootstrapping phase is dominated by data acquisition, analysis, and processing. However, this refers mainly to getting up to speed with the right tools and collaboratively developing a common communication channel – from data to design and back. It is the phase of divergence in unfolding all aspects and facets of data.

Example Case

Bootstrapping in the example case could mean that the bio-signal expert in the design team would prepare a short overview of possible sensors that could deliver data at a rate of one sample per 5 seconds without consuming too much power and being too bulky for a small wearable design. In parallel, the designer would find related research that connects sensor data to bodily phenomena such as arousal, relaxed state, or even sickness. In addition, the designer would search for examples and inspiration from related applications (cf. Figure 9).

Fig. 9. Overview of data sources for Qualica

Exploration

When exploring data in the design, we often encounter a chicken-and-egg problem that unfolds. In a situation in which data is abundant, but not immediately accessible, let alone, usable, we face the question, what can the data offer? At the same time, we need to ask, what does the design need? This problem unfolds further if more than one person is involved. Nevertheless, data and meta-data need to be shared, explained, critically evaluated, and discussed. In collaborative teams, such processes can easily stall if no means of sustained communication is in place.

Sampling: One strategy is to start with open exploration of the data itself. If it is not yet clear whether data can help us design or which aspects would be most relevant and useful, the process of starting with a data sample is a strategy to break out of this loop. Thus, this loop involves *seeding* a data exploration process. Such a seed is a small excerpt of data from a few (randomly chosen) data sources. It is so small that we can easily manage it, and at the same time, big enough that we can assess whether the chosen data sources are useful for further exploration. In a step-wise process, we can move through the available data sources and determine their value for the design challenge. This is not an easy task, but over time, a certain *smell for data* will develop and guide us towards more intuitive exploration of data. Once this step is done, we can move faster through the haystack.

Inspiration: Another strategy is to take the design challenge as a primer for exploring the data sources that could potentially inform the design process. An interesting approach is to make use of extensive inspiration material to identify similar or related designs that will in turn inform all design team members (especially the

more technical ones) what the team might be looking for in the data. If you are stuck, change the visual paradigm or the visualization that might limit you.

Comparing these two exploration approaches, both have in common that they are used to break out of a potentially stalled process and aim at gaining momentum and moving forward with the design team. Paralysis by data is an unworthy thing to suffer from in design, but it happens all the time. As one moves along this process, it is worthwhile to document choices and decisions made. Therefore, the team can fall back on earlier thoughts and decisions when needed.

The next step is to formulate a short summary of what the data sources deliver, when, and which quality. Thus, it proceeds with constructing *design information* accordingly. Especially for information that is hard to get, privacy-relevant, protected, or rare, *design information* can mean in the first phases to collaboratively analyze the data sources and to build a mock-up of fake data that closely mimics the real data without revealing the truth.

Fig. 10. Sketch of the Qualica design space

Example Case

Exploration in the example case is based on the information about sensors within the device and a couple of open data APIs on the Internet. Different stakeholders such as business or domain experts could be consulted to get a better idea of a potential market fit. Together they document these starting points in a work book and conclude the session with a short sketch of a “landscape” of potential data sources, usages scenarios and connecting visualizations: the design space (see Figure 10).

In the following exploration phase, the designer decided on the first approach to rely on the body signal data and link it to desktop application activity feeds from a desktop logging application. The sensor data is retrieved every 5 seconds. Therefore, by using the average value of a window of 40 seconds (~8 samples), a first good balance between reaction time and useful activity information was found. However, finding patterns was difficult, as the sample size of the subjects generating the data was not large enough. Application usage data was derived and mapped to different types of applications and computer usage scenario such as work, entertainment, communication etc.

Based on this exploration phase, the design team decided to continue with a rough classification of activity as the reference context for visualization instead of pursuing unreliable correlations with body signal data.

Design Iterations

At the point of design iterations, once both infrastructure and design information have been established and explored, more traditional design processes can be weighed in an iterative process alternating between design information and the design. The remaining challenges are essentially about framing the design information in a way that best fits the target users and the desired user experience. Design information needs to be packaged and tested in the context of use by applying degrees of freedom for interaction with the presented information.

Fig. 11. Example case design iterations on the minimal visualizations of activity in context

Example Case

Given the right interfaces to data and the insights from the exploration, the designer would start with a first functional prototype of the wearable interface. Consequently, a quick processing sketch was all the design team needed to get a better

understanding of the visualizations. It is much faster than working with hardware and LEDs, although the design team could quickly move towards a prototype implementation with an Arduino board. Figure 11 shows the different visual patterns for a minimal visualization of application scenarios. The left column shows how a single row of multi-color LEDs could show static information such as a progress bar, a scale, and a categorical overview of activity. The middle and right columns show how animations could indicate a specific context or context absence.

The *design iterations* benefitted from quick access to design information, and if needed, changes to the data collection and processing functions. The process figure (cf. Figure 8) shows how design information effectively separates the design from data collection and direct access to data sources, thereby preventing unnecessary complication in the overall process.

Conclusions

What we have seen in this chapter is not just an overview of the early steps when designing with data, there are stepping stones that we can use to guide our ways and not diverge too far from the original design goal. One of the most important lessons in this area is to trust in our gut feeling regarding data and the properties of a dataset, and at the same time, to question every single move. However, data and information are so abundant, but alien to us that we tend to forget the special positive traits and hidden pitfalls of the *materiality* of data. Another point is to communicate *meaning* and meta-data in the right way. Data gets meaning by contextualization, linking, and relating. This chapter emphasizes the utility of design information for *scoping* and *framing*, as data available for design can be overwhelming in quantity and quality. Especially nowadays, scoping and framing can be real problems in a data design. Thus, a clear set of design artifacts supported in the design process can help.

While this chapter focused mostly on *designing information* products as a category of more or less physicalized interactive designs that heavily rely on data and information, data design tools can be crafted in the same way with a stronger notion of reuse and generalization. The chapter was written also to balance the current emphasis on a “flat” graphical visualization of information. The potential design space around data is larger than that. It extends to physical products, apps, services, and systems that all carry the notion of communicating information to humans in an understandable, yet rich and expressive way that inspires action. Without design, this would be impossible.

Fig. 12. Qualica; final product form

Example Case

With the rich design information and some ideas in mind, the designer could start to dive into dynamic visualization of the incoming data. The design evolved naturally from simply signaling the different states in colors towards comparative views that would highlight differences between own state and the social network to the user. The design shown in Figure 12 evolved from a few displayed values towards more contextual information. It adds text and icons from the social networks, and then goes back to reduced graphical “cues”. The final design iteration was a minimal visualization consisting of several small dots, glowing and forming slow patterns over time. This concludes the early design phases, as the design was already at a stage where it could be evaluated with a few potential users.

Further Reading

In the following, a few directions for further reading will be introduced briefly. There is a recent wealth of books on data visualization of which a few are presented here. First, pure data and information visualization is introduced well in books by Edward Tufte, an early advocate of presenting information to a reader effectively. You will find that he is (provokingly) outspoken against any kind of noise that masks data or information in their presentation. Also, he is quite close to design in his approach to understand and questioning needs to visualization from a data practitioner’s point of view. A good starter is *Envisioning Information* (Tufte,

1990), with *Visual Explanations: Images and Quantities*, and *Evidence and Narrative* (Tufte, 1997) as a follow-up. More theoretical views on visualization are available from *Information Visualisation* (Spence, 2002) and *Information Visualization: Perception for Design* (Ware, 2004).

Second, there are recent books on *designing* visualizations and interaction with data, for instance, *The Functional Art: An introduction to information graphics and visualization* (Cairo, 2012), *Now You See It* (Few, 2009), or *Raw Data – Infographic Designers’ Sketchbooks* (Heller and Landers, 2014). The latter book does not only present finished designs, but looks behind the scenes and shows ways of working and translating data into masterful visualizations. Thus, a very practical guide is *Designing Data Visualizations* (Illiinsky and Steele, 2011). For an introduction into D3 as the currently most popular toolkit for visualization on the web, *Interactive Data Visualization for the Web* (Murray 2013) is highly recommended.

Other related disciplines, such as generative art can be inspiring as well. However, *Generative Gestaltung* (Groß et al., 2009) or *Design by Numbers* (Maeda, 2001) are good starting points. A growing trend entails the use of visualization techniques in journalism and media. They are however, not the focus of this chapter. Unfortunately, little work is published so far for physical visualizations (Fens and Funk, 2014). Also, multi-modal information products, which we also target in this chapter and an interesting list of physicalized visualization can be found here: <http://dataphys.org/list/>.

As for a bit more advanced reading on what is happening currently in the area of data visualization, there are three important conferences on visualization-related topics: IEEE VIS, ACM SIGGRAPH, and Visualized (non-academic) conference. There is also a relevant journal, ACM Transactions on Visualization and Computer Graphics, which publishes articles like *Mental Models, Visual Reasoning and Interaction in Information Visualization* (Liu and Stasko 2010), which are worth reading. For less academic and more practical data design resources, there is a lively community on Twitter and on different websites. Thus, be sure to check out <http://www.datastori.es>, www.visualization.org, and <http://blog.visual.ly>.

Collaboration in data visualization and interfaces mostly refers to the collaborative *use* of such interfaces and products, and not to their design or development. However, there are a few exceptions looking at what challenges research on collaborative visualization (design) has to tackle still. This is increasingly moving away from the collaborative *use* of visualization and visual analysis towards collaborative *design* (Heer et al., 2008; Isenberg et al., 2011).

A whole different area is demarked by literature on rationality, psychology, and statistics. *Everyday Irrationality* (Dawes 2002) is recommended for getting a general overview of how people experience information and interpret it (often in their favor or naively). To dive into statistics and behavioral psychology, there are again many sources to choose from e.g., *Becoming a Behavioral Science Re-*

searcher: A Guide to Producing Research That Matters (Kline, 2008) or *Straight Choices: The Psychology of Decision Making* (Newell et al., 2007).

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