LISTENING TO AN EVERYDAY KETTLE: HOW CAN THE DATA OBJECTS COLLECT BE USEFUL FOR DESIGN RESEARCH?

NAZLI CILA
DELFT UNIVERSITY OF TECHNOLOGY,
DEPARTMENT OF INDUSTRIAL DESIGN
N.CILA@TUDELFT.NL

ELISA GIACCARDI
DELFT UNIVERSITY OF TECHNOLOGY,
DEPARTMENT OF INDUSTRIAL DESIGN
E.GIACCARDI@TUDELFT.NL

MELISSA CALDWELL
UNIVERSITY OF CALIFORNIA SANTA CRUZ,
DEPARTMENT OF ANTHROPOLOGY
LISSA@UCSC.EDU

FIONN TYNAN-O'MAHONY
UNIVERSITY OF EDINBURGH,
SCHOOL OF DESIGN
FIONNTOM@GMAIL.COM

CHRIS SPEED
UNIVERSITY OF EDINBURGH,
SCHOOL OF DESIGN
C.SPEED@ED.AC.UK

NEIL RUBENS
UNIVERSITY OF ELECTRO-COMMUNICATIONS,
CENTER FOR SCIENCE AND ENGINEERING
NEIL@HRSTC.ORG

ABSTRACT

In the current Internet of Things (IoT) environment, objects are tagged with sensors without a clear understanding of people's individual and collective patterns of behaviour. We argue that designers can create more meaningful and effective networked objects through collaborating with ethnographers and Machine Learning (ML) experts. In this paper, we present the approach and preliminary insights of two analysts from those disciplines on the same data set, and speculate on how they complement one another and the design process. Ethnographic data can indicate the questions that are interesting to study with ML algorithms and help interpret the data generated by ML by positioning it into wider socio-cultural situations. Ultimately, this collaboration can inspire designers to create meaningful products, services, and processes of IoT.

INTRODUCTION

Connecting wireless communications technology to products aided the appearance of "networked" objects. With the help of sensors, refrigerators, bicycles, thermostats, and even toothbrushes have began to communicate with their owner, manufacturer, and of course, one another. This "Internet of Things" (IoT), a term coined by the Auto-ID research group at MIT in 1999 (Ashton, 2009), refers to the emerging system of products becoming connected to the Internet. This system enables data to flow between people, networked objects, and Internet services and has begun to allow us to explore and shape our surroundings in a way that is unprecedented in both speed and scale.

The amount of data that is being streamed from networked objects is massive. As such objects become more common, the data they will collect will soon outweigh what we know about the physical object itself (Speed & Barker, 2014). This situation, however, raises some concerns. In the current IoT environment, there seems to be a race to tag every product with a sensor without the guidance of a clear user experience or business model (Claro Partners, 2014). But without new methods to understand and tap into people's patterns of behaviour, webs of practices and emerging values, it is hard for designers to imagine and create meaningful networked objects (Giaccardi, Speed, Ruben 2014). Our main claim in this paper is that these new methods can be developed only through close collaboration between designers, ethnographers, and computer scientists.

Objects circulate in "regimes of value", which belong to specific temporal and geographic settings (Appadurai, 1986, p. 4). The shape and meaning of objects are assigned through their incorporation across diverse environments. We consider that ethnographic research and Machine Learning (ML), which are both *pattern seeking* in their simplest sense, can contribute to reveal this complex architecture of practices and values. ML algorithms have already being used to cross-reference a multitude of databases and identify common patterns across a large variety of situations (Bandyopadhyay & Sen, 2011), and current ethnographic design research methods are well equipped to position patterns in specific socio-cultural situations, thus offering in depth insights and understandings of those patterns. Together, ethnographers and machine learning experts could provide the relevant quantitative and qualitative data that is needed to guide and enrich the creative process of designers who work in the IoT space by providing them detailed knowledge about the use, value, and meaning of objects and their relevant practices.

The aim of this paper is to contrast and combine these two approaches through discussions with expert analysts, and investigate the usefulness of the approaches for design practice and research. In order to do so, we generated a novel type of data set from the use of three products at five households. We then discussed this data set with an ethnographer and a computer scientist with an expertise in ML about how they would approach to analyze the data and what kind of patterns they would expect to find. In this paper, we first present the theoretical and practical issues that were pointed out by our experts, and then discuss the relevance of these issues to design research in IoT.

SEEKING PATTERNS IN DATA

Law (1991) speaks of the ontological symmetry of people and things, where objects adopt the characteristics of humans by forming networks, speaking, and working performatively. This style of analysis inevitably questions the dominant divides between subjects and objects, and between ideality and materiality (Engeström & Blackler, 2005). This is especially the case with networked objects since they take on agency through the data they collect and interventions they make in the lives of the people that use them. However, the focus of the research conducted within IoT domain so far is exclusively human-centered: Products and services are meant to answer the needs of people only. Yet there is an ongoing "dialogue" between people and objects, a consensual relationship about an object's function and value that develops in use, which call for methods of design research that give both people and objects an equal voice. We argue that within an IoT paradigm, it is crucial to include objects into the research process as participants (not just as products) and make better use of the data they gather while being used, sitting and moving around us. This data can be numerical, and thus readable by computer codes, or can be qualitative so to reveal the practices developed around the object within specific socio-cultural situations.

McVeigh-Schultz et al. (2012) used lifelogging (i.e., a video record of personal information) as a way to capture the perspective of networked objects, and explore new design opportunities by animating objects as characters with their own stories to tell. We followed a similar lifelogging approach to build our data set and provide both our analysts (i.e., the anthropologist and the ML expert) with a rich source of information and potentially novel insights.

THE DATA SET

Considering the notion that practices are carried out within familiar contexts, temporal orders and objects (Ng, 2013), we selected a mundane home activity—preparing and drinking tea or coffee—and focused on the practices that revolve around a kettle, a fridge, and a cup (k-f-c). It was thought that together these objects would reveal insights not just about themselves but also about their relationships with each other, that is, about interconnected practices.

We attached logging devices called Autographers (www.autographer.com) on k-f-c sets at five households to capture visual and numerical data about patterns and movements of objects at use time (Figure 1). Autographers are small cameras that are clipped to a person or object and automatically take pictures when prompted by one of the sensors embedded in them (accelerometer, color sensor, magnetometer, thermometer, and PIR). The Autographers provide time-lapse details that can be accumulated into a visual narrative of events, as well as record numerical data of each event.

Figure 1: Autographers at work.

Each household was given three Autographers for two days. On Day 1, the Autographers were placed on the kettle, cup, and fridge, and on Day 2, they were placed on the kettle, the cup, and the user. The users were asked to turn on the Autographers only when they prepared coffee and tea. By this way, we ensured that the Autographers did not take any photos without the users' awareness and will. The procedure involved introducing the users with the Autographers, explaining the procedure and getting consent, asking them to prepare a tea or coffee to check if the cameras worked as well as to provide a base to talk about their tea and coffee routines. We ended the procedure by interviewing the users about their coffee/tea practices and related products.

Data collected from the Autographers provided detailed information about the use patterns of particular objects and their trajectories throughout space and time, and supplemental data on parallel activities and objects. The Autographers collected 3000+ photographs, which were combined in a timeline (Figure 2) to be discussed with our analysts.

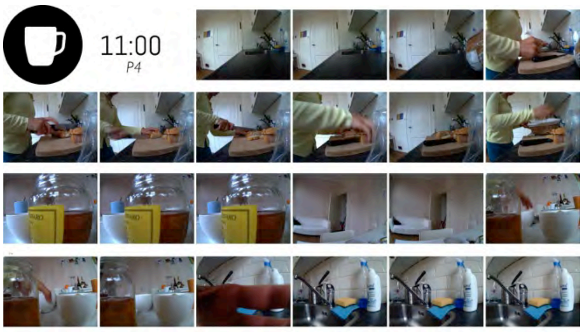

Figure 2: Format of the photographs taken by Autographers (from a cup's perspective)

PATTERNS FROM AN ETHNOGRAPHICAL PERSPECTIVE

Involving ethnography within design is not detached observation; rather it helps unfolding practices and closing the gap between observation and understanding (Gunn & Donovan, 2012). Ethnographers illustrate the intimacy of relations between the material and the social, and the complex relationships between objects and values. Their role is to reveal differences and similarities in order to allow people have a better way of knowing what they do (Leach, 2010).

The preliminary interpretations of our first analyst, the anthropologist, mainly revolved around understanding how the objects were used and valued, and their relationalities with other objects and practices. For this project, the ethnographic approach would begin with triangulation of different types of data gathered from different methods: visual and aural data gathered through real-time observations and photographic images, reported data from human subjects via interviews, and comparative knowledge about material practices – notably use of appliances and kitchen cultures – from previous ethnographic research in other contexts. By considering data both discretely and collectively, the analysis would identify not just rituals and patterns of use, movement, and time, but also points of commonality and difference across the sites studied here, as well as possible commonalities and differences with other contexts outside this particular study. As a result, the ethnographic data would be useful for considering issues of scale and scalability, embeddedness of practices and beliefs within particular cultural contexts, cultural modes of temporality, particularity versus generality of practices, and comparative possibilities beyond this particular research.

Specifically, in looking at the data, the anthropologist was interested in understanding some fundamental questions: (1) What were the objects that inhabited the settings studied and what were their basic properties or behaviors (were they human, non-human; did they move or remain in one place; how did they move and under what conditions; did they change or remain the same; what was the nature of change); (2) What were the relationships among these objects (how did they interact with one another, how were those interactions apparent; did there seem to be any sort of patterning in terms of sequencing, repetition, preferences, or motivation – such as deliberate interaction, accidental interaction, spontaneous interaction, byproduct interaction); (3) How did human subjects describe the quality of those interactions (what terminology did they use, what features did they remark on or not remark on); (4) What commonalities or differences appeared across the different types of data (did human subjects use an object repeatedly but describe it as rare in the interview; did the interviews focus repeatedly on an object or practice that did not appear in the photographs); and (5) What exceptions, contradictions, or curiosities emerged. From these initial questions, the anthropologist could draw initial hypotheses about such concerns as value, beliefs, social relations and social networks, implicit and explicit knowledge, and individual versus cultural or collective traits, among others. We detail a few hypotheses from these materials here.

On the basis of the photographs taken by the Autographers, the first fundamental issue that our analyst pointed out is the curious distinction between static and dynamic objects: some objects travel while others remain in place. And as such, they each belong to different, although at times overlapping, communities of things. We see all kinds of things moving into and out of the photographs, e.g., fresh produce, plastic bags, cutlery, kitchen towels, and see the things that move and come into contact with other things. For instance, for cups that move, they go in cars, which brings them into contact with radios; when they go to work, they come into contact with laptops, books and papers, and so on. In other words, it is apparent from the photographs that objects exist in longer chains of relationships with other objects and practices. This evokes the ideas about where things "live", where their "homes" are and which things live where. Therefore, we need to think about neighbourhoods and communities and how those are connected physically, socially, and emotionally. There may be things that have homes, which are not where they appear to be. It is interesting from an ethnographic point-of-view to map out these relationships to see what interacts with what and theorize about whether movement changes the nature of things and the social ecologies they inhabit.

In addition to the objects' movement through space, there seems to be interesting work about temporalities as well—things exist in specific temporalities but not necessarily the same temporalities. For instance, it seems as if most people do other things while they wait for water to boil and coffee to be ready (Figure 3). So, things occupy time, but also create empty times for other things. A kettle occupies time, but that is time that the person making the coffee is not using for that task, so the person does something else during that time to make a phone call, do push-ups, wash dishes, etc. Objects and users may occupy different temporalities and may engage in different types of activities and assign different values to those temporalities. In many respects, the temporal rhythms of things force users to adapt their own temporal rhythms, which open up intriguing possibilities for understanding how things are both mechanical and social actants in the world. While these practices are occasionally captured by the Autographers, they are rarely captured by the interviews.

Ultimately, the initial analysis of our first analyst helped to distinguish between different spatial trajectories and temporalities of objects while also revealing the multiple, overlapping, or even parallel relationships that cohere among the objects.

Figure 3: Things done while waiting for the water to boil (from a kettle's perspective)

PATTERNS FROM THE ML PERSPECTIVE

In machine learning there is a subfield that focuses on the task of discovering patterns, namely pattern recognition. Each observation (data point) is typically considered to be multi-dimensional (multiple attributes/features). For instance in our dataset, each photograph may be considered to consist of: the photograph itself (pixels), time and date of the photograph, location, and so on. Other attributes could be extracted by utilizing variety of analysis techniques, e.g., using computer vision techniques to identify one or several objects or object classes, identify specific people in the photographs, or detect specific conditions and situations. To provide contextual information, additional attributes could be obtained by linking with external datasets, e.g., using GPS coordinates and time/data of the photograph, it is possible to obtain the data on the weather, local events, and so on.

The ways in which pattern recognition is performed can be classified as supervised and unsupervised. Supervised learning can be used for discovering patterns by specifying for which attribute should the patterns be discovered. Any of the attributes could be at the center of the inquiry; e.g., kettle being on, type of drink being made, time of the day, and so on. Once the attribute is selected the algorithm looks at other related attributes as to discover variety of patterns. For instance, in the case with the kettle being on there might be patterns that include time of the day (everyday between 8 am-9 am), presence of certain individuals or objects (such as cups on the counter; see Figure 4), and actions (such as opening the fridge). Unsupervised learning is a broader pattern search technique in which the algorithm decides for which attributes the patterns will be discovered.

Figure 4: Identified cups which enter the scene (from a kettle's perspective)

By utilizing ML, a multitude of patterns could be discovered. However, many of the patterns might not be as meaningful. For example, ML may find a variety of obvious patterns for "the kettle being on": kettle is on when the kettle indicator light is red, kettle is on if the water level is not empty, kettle is on if it is not dark in the room. From the ML perspective all of these patterns are very strong, yet in practice many might be of no value. In ML the degree to which a pattern is considered "interesting" is typically determined from a purely quantitative standpoint. However, while most patterns might not be as useful, some might provide an interesting insight which might not have been discovered otherwise (e.g., every instance that the kettle is turned on, there is a particular advertisement at the TV). How to interpret and make use of this pattern are at the hands of designers.

Ultimately, the multitude of patterns produced by ML could expose designers to a variety of aspects. In turn, feedback from examination of these patterns could be incorporated into the ML algorithms as to make the search for patterns more efficient and useful.

COLLABORATION BETWEEN DISCIPLINES – RELEVANCE FOR DESIGN

The movements, lives, and transformations of objects are complex, but we consider that they can be subjected to reasonably systematic and rigorous analysis through a combination of ethnographic studies and machine learning algorithms, which would be used as a basis for coming up with design concepts and innovation potentials by designers.

Of particular concern to ethnography is to investigate the motivations, beliefs, and values that inform people's behaviours and the objects they use in these behaviours, especially in terms of understanding discrepancies between reported and actual behaviour. Design does not have a sustained tradition of theorizing the context of usage and interpreting the cultural meaning of things. The forte of ethnography is contextualization, holistic explanation, and cultural interpretation through cross-cultural comparison and the development of theoretical concepts (Otto & Smith, 2013). Therefore, it provides an analytical frame to understand practices from which design requirements and ideas may be extracted (Kjærsgaard, 2013).

The data gathered through ethnographic research can help identify gaps and contradictions, and ultimately initiate critical inquiry into issues of generality and specificity, routine patterns and deviations from norms. The issues that were raised by our ethnographer analyst about the temporality, movement, and relationships of objects, for instance, can be used as a new perspective to think about objects. Imagining the time perception of objects (e.g., what would empty or filled time look like from the perspective of an inanimate thing? what are the multiple routines and rhythms that exist between and across the things that are in relationships with one another?) or social dynamics within a context (e.g., how does the nature of the relationships change when an object moves between different users or the same user moves between different objects from the same category?) can bring unique insights about the role of objects in human practices, and thus open up design opportunities that we may not be able to foresee with traditional methods of user research. In a former study, we used such questions posed from an ethnographic perspective as an exercise to look inward to the imagined character of objects and outward to the larger social context that surrounds them, which inspired designers to come up with novel design ideas (Cila et al., 2015).

The main contribution of ML to the design field, on the other hand, is expanding the processing of the data gathered by objects beyond human capacity and skills. ML could be used as a way to identify novel patterns of use within the data that is streamed through the interaction between people and things, and things and things. Through a better understanding of what data can tell us about how we use objects in practice, new models of use may emerge and inform the development of exploratory design concepts and prototypes. Second, the complex constellations of objects, data sets gathered in realtime, and ML algorithms that identify patterns constitute openings together to new markets where different kinds of "value" are exchanged (Speed & Barker, 2014). For instance, the Google Nest thermostat learns how you live through data gathering and analysis, and promises to save you energy and money. In this case, the data produced through personal and social activities is exchanged into value to constitute new market content. Third, ML algorithms can also help designers to predict futures—once appropriate patterns are identified predicting future might be just a matter of performing extrapolation (Armstrong, 1984).

In all the cases that have been mentioned so far, it is apparent that each discipline has strengths that can make a unique contribution to the design field. For example, while ethnography provides data explaining "social facts" (Durkheim, 1982, p. 50-59) of processes/practices and positions them in a wider socio-cultural situation through interpretation, the data provided by ML algorithms is "objective facts", focused on instances and gathered faster. In order to reach to meaningful outcomes, ethnographic research requires a small number of data points, whereas ML requires a lot of data points from multiple situations and a bigger group of people. This provides ML to cover a "breadth" of all relevant issues for a context and ethnographic research to offer "depth" on specific issues.

The ethnographer plays an active role in data collection and analysis, whereas the role of computer scientist is more passive when analysing the data. This may help the computer scientist to reveal some patterns that were invisible beforehand, yet s/he needs the help of the ethnographer to make sense of those patterns (Kriegel et. al., 2009). In other words, it is more difficult for an ethnographer to see patterns that are at larger scales than captured by the ethnographic data, whereas a computer scientist cannot see which patterns are meaningful. And lastly, provided by the approaches used by these disciplines, the patterns revealed by ethnographic research are higher in "quality" while they are higher in "quantity" in ML. These qualities are summarized in Table 1.

Table 1: The qualities of the ethnographic and ML data

Ethnographic data	**Machine Learning data**
Involves *interpretation*	Based on *factual* situations
Positioned in socio-cultural situations	*Non-situated*
Requires *a small number* of data points	Requires *a lot of* data points
Provides *depth*	Provides *breadth*
Active data collection	*Passive* data collection
Focused on *processes* and *practices*	Focused on *instances* and *moments*
Identifies *existing* patterns	Identifies *invisible* patterns
Revealed patterns are higher in *quality*	Revealed patterns are higher in *number*

Provided by their complementary strengths, we consider that a combination of these disciplines affords excellent grounds for designing for IoT. The working relationship of ethnography and ML can be in two ways (Figure 5):

First, ethnographic data can point out which questions and practices are interesting and rich to study and ultimately have a potential to trigger design ideas (1a). This involves theorizing about particular contexts to look into or conducting field studies to identify which objects to collect data from through sensors and what parameters to keep track of. This is essentially a question of what inputs matter and why, in a certain situation. Guided by ethnographic studies, the ML algorithms can then go through the data collected through those objects and reveal some patterns (1b).

Second, ethnographic research can also help in interpreting the data generated by ML (2a, 2b). Sensor-based data and its related analyses are often not, in itself, directly informative of the activities and contexts, and automatic interpretation often cannot adequately reflect the situated and contingent nature of human activity (Dourish, 2004). Using an ethnographic perspective can help to understand the full meaning and context of this human activity in open-ended domains. In both processes, the outcome of the analyses from each discipline can be the input for the other.

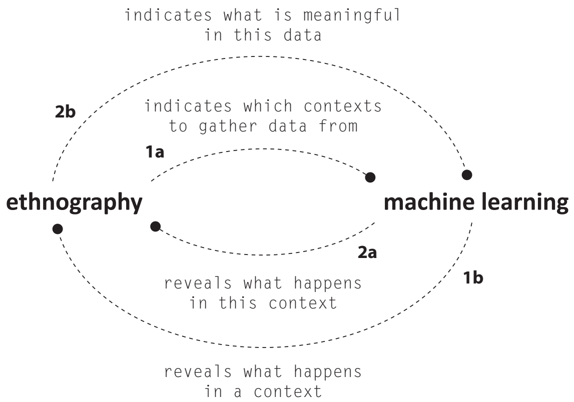

Figure 5: How the disciplines of ethnography and ML feed into each other.

Design is directed toward the future. Its success is demonstrated by the relevance of its outcomes to people's lives and material and social impact of particular solutions, rather than by the validity of its generalizations (Otto & Smith, 2013). This is the point that design departs from ethnography and ML. It does not aim for all-applicable solutions that are based on existing data, but for products and services that can transform reality. The patterns revealed by ML and ethnography about human behaviour and object use can provide inspiration for designers, yet they need to go one step further by transforming this knowledge into meaningful products, services, and processes. To put it differently, the aim of ML and ethnography is not simply to provide designers with more information about use practices, but rather to inspire them to explore new cultural practices by understanding the overlaps and gaps within current practices and beliefs with a view of instigating behavioural change around the employment of data.

Designers are certainly required to *adapt* the patterns revealed and the relationships identified into meaningful user experiences and business opportunities with their expertise. A failed example in this sense can be Audrey (Figure 6): Seeing that the kitchen is considered as the heart of the home by many people and recognizing that people do lightweight web browsing or "Internet Snacking" when spending time in this environment prompted designers to come up with the idea of Audrey, which is a digital assistant located in the kitchen combining an agenda, an address book, and a calendar, and has Internet access for checking the weather and the stock market (3Com Audrey, 2015). Not surprisingly, Audrey was discontinued soon after its introduction in 2000. Its short life offers us a lesson about combining different user activities (spending time in the kitchen and surfing Internet, in this case) without considering the bigger use context and market demands. Audrey became yet another countertop appliance that did not help its cause, rather than a meaningful product answering a real user need. The task of the designers is to integrate the patterns identified by ethnographers and ML algorithms into their design processes by considering the bigger use context and envision new futures on the basis of the value architectures revealed by these disciplines.

Figure 6: Audrey by 3Com.

CONCLUSIONS

Generating new products is, "a practice of configuring new alignments between the social and the material that are both localized and able to travel, stable and reconfigurable, intelligibly familiar, and recognizably new" (Suchman, Trigg & Blomberg, 2002, p. 164). In the IoT environment, we consider that it is possible via collaboration between ethnographers, ML experts, and designers. Through fieldwork, ethnographers can tell ML experts where to look at interesting patterns and/or make sense of the patterns identified by ML algorithms. By integrating this knowledge into their concept generation process, designers can envision more accurate futures, as well as more meaningful networked objects.

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