Making Machine Learning Tangible for UX Designers

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ABSTRACT

There is considerable current research interest in the relationship between machine learning (ML) and user experience design (UX). This comes both from design researchers within the human-computer interaction (HCI) community, who have sought ways for UX designers to work with ML, and data scientists in new types of collaborative practice. The need for a shared language between designers and data scientists has emerged as a key factor, with the creation of boundary objects in the form of sensitising concepts seen as a useful approach. This paper presents original research that responds to the call for such concepts by working directly with UX designers to model aspects of ML technologies in physical form. Our intention is to position designerly abstractions as examples of the type of boundary object able to bridge the domains of UX design and data science and open up new possibilities for the design of ML-driven digital products.

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KEYWORDS
Machine learning; User Experience Design; Design Research; Boundary Objects; Sensitising Concepts.

CSS CONCEPTS
Human-centered computing; Scenario-based design

INTRODUCTION
Existing collaborative practices in the field of Machine Learning technologies tend to have a data-first character with UX design seen as an end point of the development process. This is evident in services as diverse as, game design [11], banking [3], and identity authentication [16]. UX has been slow to respond to this imbalance in the process and struggles to make the argument for a design-oriented approach, perhaps as a result of the difference between the mainly quantitative knowledge traditions of data science and the more qualitative approaches of design [7]. This data dominance of the production process is exacerbated by the complexity and opacity of the technical implementation and the probabilistic nature of the outcomes.

This paper reports on a pilot study carried out with a group of twelve user experience, interaction and interface designers modelling their understandings of the effects and possibilities of machine learning. The aim was to sensitise designers to the creative design possibilities of digital products and experiences driven by ML algorithms. The pilot study was developed over two months and culminated in a day-long workshop.

BACKGROUND
This brief review focuses on research from HCI describing the relationship between user experience design and machine learning. With it, we intend to show that this is currently a relatively undeveloped field of research.

Dove et al. [5] highlight the challenges to designers of working with ML as a design material. Their survey of 51 participants reveals that UX designers consider ML to be complex and technically obscure, and therefore difficult to create new designs with. Dove et al.'s survey also shows that these designers are concerned about the ethical implications of ML and the cost of incorporating it into their work. Holmquist [8] lays out conceptual aims for designers to mitigate some of the unforeseen effects of AI such as unexpected results, the impossibility for the system to be fully explainable, and the constantly evolving nature of algorithmic systems.

Girardin and Lathia [7] show how the relationship between UX designers and data scientists is redefining what we mean by user-centred in design, by prioritising data over users. Yang [19] points out that exploration of the idea of ML as a design material is very different to technical HCI work 'which typically uses ML as a tool to extend or accelerate well established interaction forms'. [19], 468]. She explains that there is a 'clear need for design research that helps expand designers' perceived application of ML, and sensitises them to the breadth of its design possibilities' [19], 469]. She makes the argument for 'a kind of abstraction that focuses on the match of contextual capability and user value; a kind of taxonomy that is likely to be radically different from ones used by data scientists [19], 471].

Designers, according to this argument, should develop ways of making a distinctively design-oriented case for themselves in the field of ML-driven digital products. Yang et al. [21] go further to show that designers with experience working on ML-driven systems regularly use what they call ‘designerly abstractions’ to explain the possibilities of ML and communicate between themselves. They highlight that this is an exploratory, imaginative process that challenges designers not to understand the technical workings of ML, but to ‘envision applications technologists would likely never imagine’. Yang et al. also propose ‘sensitising concepts’ – designs created to open up the space for design innovation through which designers can explore the imaginative possibilities of ML. Both designerly abstractions and sensitising concepts act as boundary objects [14] for communicating between domains. Although now sometimes seen as diagrams and drawings, in this study we explicitly reconnect the original designation of boundary objects as material three dimensional objects [14]. Yang et al. [20] explore sensitising concepts in more depth, explaining how they are used by designers to push the boundaries of a design space, and by design researchers as a way of producing new knowledge.

We report results from a participatory workshop that sets out to facilitate the creation of such sensitising concepts in the form of designerly abstractions. Where we develop new knowledge is through our emphasis on the use of physical materials to do so.

METHODOLOGY

The aim of this pilot study was to find out how UX designers responded to the idea of designerly abstractions, and more specifically how physical materials might provide for creative exploration. It is explicitly participatory, in order to feature people transforming, and being transformed by their interventions [1], in this case, physical and material ones. As we also wanted to look at how design agencies might adapt to the challenges and opportunities represented by ML technologies, we designed and facilitated a day-long workshop with designers from a leading London design agency. Twelve designers, with no direct experience of working with ML, participated in the workshop, six men and six women from all levels in the organisation. They collaborated in three groups on the workshop activities which took place in three stages. Participants were aged between 22 and 63.

Method

Participants started by listing some of the positive and negative aspects of digital systems driven by machine learning. The aim was to do a simple analysis of what participants thought were the important characteristics and effects of ML driven systems.

The second phase involved participants making models representative of their ideas of the effects of ML – designerly abstractions, using two-dimensional physical materials including coloured acetate, paper, card, and coloured stickers. These were chosen because their contrasting qualities of transparency / opacity, dark / light and flexibility / rigidity meant they could be combined to

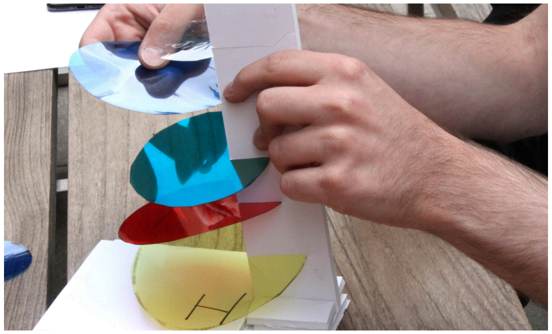
Figure 1. Disc sequence

Participants created a model which enabled discs of coloured transparent acetate to be layered in a specific sequence. The discs had different diameters, and could be ordered in any way the designers chose. The object was roughly 20cm high, made of white foam board and featured a square base so that it could stand on a table top without being held.

Participants explained this model as representing personal data in the form of “bubbles that could expand or decrease... different things fluctuate based on your experiences and your interactions with the AI and with other people”. The effect of this would be that “The version of you that exists is relative, depending on all the other things that are in and around you. So there is no one you, there are twenty versions of you”. The concept thus allows people who are using digital systems driven by ML to make their identities more layered and nuanced and eventually so complex that an individual is no longer discernible.

represent opposing values. The aim of this phase was to transform the written ideas into tangible, substantial forms around which a new set of understandings could coalesce [6] [15].

The final phase of the workshop required participants to imagine speculative digital products in which their observations and thoughts about machine learning could be implemented. The aim was to freely explore how sensitising concepts could be materialised in physical forms and then shared and discussed. Materials for this final phase were fully dimensional and included felt strips, cork spheres, wire, paper straws, modelling clay, and beads. These materials were chosen for the ways they could be combined and because they allowed for a wide range of metaphorical representations.

Why physical materials?

The physical nature of the materials allowed participants to bypass usual design reasoning, gave limitations that were liberating and added an alternative cognitive dimension to the exercise. The use of materials also enabled a direct mapping between metaphorical and the physical: and opened up participants' abilities to conceive the imaginative potential of ML technologies. Physical materials were seen to be easy to work with, affording new ways of communicating and thinking.

This echoes findings from similar work [6] modelling experiences of digital systems. Making physical representations closes the gap between abstract and concrete while allowing complexity to emerge. Physical models allow for the development of new metaphors, which can be a critical way for designers to communicate their internal understandings of digital technologies by creating external forms. Kirsh [10] finds that ‘the materiality of external representations provides affordances that internal representations lack’ [10], 448]. Brandt [4] explains how tangible models support design collaboration, while Mäki [12] ascribes a distinctive indexicality to physical models in the way that they provide access to otherwise difficult to perceive phenomena.

Data collection

While participants made their designerly abstractions and models, their actions, material choices and outcomes were documented visually by taking photographs. Pierce [13] describes how photographic documentation plays a significant role in the documentation of research artefacts and activities. At each stage of the workshop, participants were encouraged to discuss what they had done and reflect on the process. These discussions were recorded and transcribed. We used audio recording in sympathy with Ardito et al. [2] who demonstrate its usefulness in studying UX practice in real world situations.

Data analysis

Firstly, Transcripts of participant explanations were annotated by highlighting words and phrases, paying specific attention to mentions of material characteristics. Secondly, spoken descriptions were compared to images of the models produced by participants and cross referenced. For example, when


Figure 2. Data cape

Two participants made a poncho style costume out of a white sheet, bubble wrap, coloured acetate, and felt strips. Onto this base they taped magazines, toy fruit, straws and paper discs. The participant wearing the costume thus gradually built up layers of wrapping material with subsequent additions in the forms of physical objects attached with duct tape.
They described this costume as “a shroud of who you are” based on something more intelligent than music choices. An accumulation of personal data values that "you might just cast off to be someone new.” They also intended to make a comment about how digital systems that use ML technologies to define individuals based on their digital behaviours are not distant and abstract but are intimately connected to our bodies and physical presence.

a participant mentioned wood and plasticine in the transcript, this was verified with the image of the model they had made. Thirdly, the models themselves were analysed for their material qualities, such as wearability or adaptability so as to capture characteristics not revealed by images. Finally, these three data sources were brought together and re-examined for the metaphors they embodied. For example, one model used an abacus to represent the relative scales and levels of decision making in an algorithmic judicial system. The next section describes two examples of sensitising concepts developed during phases two and three of the research workshop. Phase one, a card sorting exercise, was intended as a quick analysis of participants’ perceptions of ML, and so is not the focus.

DISCUSSION

The goal of this pilot study was to explore the validity and value of sensitising concepts in the form of physical designerly abstractions. This is suggested by Yang et al. [21] and is intended to make ML accessible as a material to UX designers. We built upon their ideas by choosing to use physical materials instead of writing or diagramming, because of their ability to create new understandings [6] [15]. These three-dimensional materials are intended to be used by designers to develop sensitising concepts and ultimately to act as boundary objects in the development of a shared language between UX designers and data scientists. Participants’ interpretations of the final workshop outcomes can be summarised as *countering illusions, revealing hidden effects*, and *challenging design practices*.

Countering illusions

Participants felt that one of the main factors in experiencing ML-driven systems is that they project an illusion of accuracy and efficiency, able to produce insight beyond the capability of human intellect. The designerly abstractions produced during the workshop featured ways of demonstrating uncertainty, emphasised ML’s frequent dependence on training data, and foregrounded the conditional nature of computational systems. The use of physical materials contributed to this interpretation because participants were forced to improvise temporary fixes and solutions. This study shows that UX designers are aware of the background problematics in the relationship between ML-driven digital experiences and the people who use them. They are also open to the need for designerly methods that may help to address them.

Revealing hidden effects

The hidden personal and social effects of ML systems are emergent. Participants admitted to only a vague understanding of the technical operations involved in building or analysing ML systems, but the implications for identity, privacy, reliability, and trust were clear. Participants nevertheless explored the tendency towards reinforcement of errors observable in ML systems and their representations showed how design might prepare users for these effects. Limitations of time and materials precluded a deeper contextual analysis, but the participants were able use their models to represent how people, devices, network infrastructure, habits, and understandings co-exist in dense entanglements. The predominance of identity-based personalisation effects in the sensitising concepts produced, such as *Disc Sequence* and *Data Cape,* shows how the limited existing applications for ML technologies in digital products constrain imaginative exploration. In this sense, the creation of physical sensitising concepts here enabled a critical exploration of existing technologies.

Challenging design practices

The creation of designerly abstractions using physical materials was new to participants. They were accustomed to develop new ideas and structure collaborative brainstorming around text-based annotation of coloured sticky notes. These are typically grouped according to themes to allow patterns to emerge. The challenge of making physical objects brought up a much wider range of metaphors and emotional resonances than they had expected. Similar work details the advantages of avoiding writing and screen-based activities to explore digital experiences with people [6], and of the limitations of language in understanding experience [9].

For one participant, using playful physical materials had a positive emotional effect: "Using different childlike materials to talk about [ML] does... make you feel like [designing for it] could be a bit more joyful" and allowed for reflection on working practices. The emotional affordances of materials are highly individually and culturally specific, but a direction for further research is to counterintuitively approach highly complex topics such as ML from childlike or even nonhuman perspectives; alternatively, Walker and Fass [18] explored reversing perspectives to see human activity through a computational lens as a critical design practice.

CONCLUSION

In this paper we reported on a participatory research workshop which aimed to explore the potential for sensitising concepts in the form of designerly abstractions to make ML technologies more available to UX designers. We built upon previous work by introducing the use of physical materials and situating the workshop in the real-world setting of a design agency. Our findings provide a basis for the creative exploration of the relationship between UX and ML and suggest ways of making this exploration tangible and interactive. This approach raises some interesting questions. How should designerly abstractions be communicated and shared? How should they be incorporated into the collaborative working practices of data scientists and designers? We also acknowledge the limitations of our small sample group of UX designers and and the limited time frame. There are many directions this research can take and we support the establishment of a community of practice around these questions. The next step for us will be to carry out a similar participatory workshop with participants from UX and ML working together.

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