UX Design Innovation: Challenges for Working with Machine Learning as a Design Material

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ABSTRACT
Machine learning (ML) is now a fairly established technology, and user experience (UX) designers appear regularly to integrate ML services in new apps, devices, and systems. Interestingly, this technology has not experienced a wealth of design innovation that other technologies have, and this might be because it is a new and difficult design material. To better understand why we have witnessed little design innovation, we conducted a survey of current UX practitioners with regards to how new ML services are envisioned and developed in UX practice. Our survey probed on how ML may or may not have been a part of their UX design education, on how they work to create new things with developers, and on the challenges they have faced working with this material. We use the findings from this survey and our review of related literature to present a series of challenges for UX and interaction design research and education. Finally, we discuss areas where new research and new curriculum might help our community unlock the power of design thinking to re-imagine what ML might be and might do.

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UX practice; design material; machine learning; interaction design;

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H.5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous;

INTRODUCTION
Technology often enters the market in the form of a technical advance, and without much concern for design. As the technology matures, designers work to re-understand it and to invent new forms not imagined when the technology was first invented. Music players offer a simple example of maturing technology. A relatively simple turntable will play vinyl records, but design innovation brought the Radiogram as a centerpiece for living rooms, the Dansette to define teenage bedrooms, and Technics SL1200s to drive club culture. Similarly, cassette recorders offered an advance over reel-to-reel, making media easier to handle and more stable during use. Designers helped to innovate this advance by bringing to life boom boxes, auto tape decks, and the Walkman. Further technical advances led to the first solid-state media players, followed by many different MP3 players. Design innovation brought about the combined experience of the iPod and iTunes service; followed by all of the devices that paired with the iPod. Technical advances in networking led to streaming media that enabled broadcasting across the Internet. Designers are now helping develop many new forms of music player including services like Apple Music, Pandora and Spotify; that challenge the idea of owning music at all. In each of these cases, a technical advance triggered an opportunity for design innovation to generate a wealth of new products.

We see machine learning (ML) as a not so new technology that is ready for design innovation. ML is neither arcane nor obscure, with numerous textbooks [21,54], introductory articles [16] and online resources [24] covering the topic. It has been an area of active research for at least fifty years [47,48]. News articles on "Big Data," the digitization of industries like healthcare, the increasing use of analytics in business and politics [e.g. 20], the spate of recent articles about the impending driverless car future, and recent developments in techniques such as deep learning [29], have raised ML's public profile. This, combined with an increasing number and popularity of online services and mobile applications that leverage ML to offer exciting new services, has led some user experience (UX) commentators to speculate that ML is the new UX [6], and to highlight ML algorithms as being "where the action is" [12]. Apps and online services regularly detect and filter spam, rank or curate media feeds, make predictions such as estimated driving times, translate speech to text, and autocorrect people's typing through the use of ML. It is no longer enough for UX designers to only improve user experience by paying attention to usability, utility, and interaction aesthetics. Instead, the best user experiences may come from services that automatically personalize their offers to the user and context, and systems that leverage more detailed understandings of people and the world in order to provide new value.

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Because ML is becoming an increasingly commonplace feature of new interactive systems, we should now expect UX designers to regularly instigate innovative products and services. They should be generating many new forms that have not been imagined by the engineers who focus on making the technology work. However, in our experience to date, we have rarely seen a UX team conceive of an entirely new way to use ML and then taken this to a development team to implement. It has been our perception that UX design teams are simply "putting lipstick on the pig" [13:7]. So we sought to better understand UX designers' participation in the creation of new intelligent products and services; and to identify where potential obstacles to this may lie.

We suspect that one reason we might see less design innovation with ML than with previous technology is that ML is a more difficult design material to work with. Unlike heuristic driven systems, ML is very different from human intelligence. It applies statistical methods to produce output that can be difficult to explain, and that make seemingly bizarre errors due to a lack of common sense [60,61]. UX designers may therefore struggle to make designs that bridge the ML and human perspective. Another reason might be the lack of education on how to envision products and services that exploit ML. UX design education programs and UX design practice resources almost all talk about designing for mobile as distinct from desktop. However, these programs and resources make little if any mention of how designers should work with ML. UX designers also lack prototyping tools for working with ML. They have tools for prototyping responsive web services and tools that make it easy to simulate the behavior of an app on a smartphone, but they have nothing that helps them quickly prototype and understand the UX impact of false negative and false positive responses from a ML service. Finally, it might be that UX designers lack a clear understanding of what ML is and what it can do. Recent UX articles on the web, where UX designers talk about ML, often reveal huge misconceptions around what ML can actually do, with many designers treating it way too much like magic.

We believe that ML currently represents an under-explored opportunity for ideation and innovation led by UX design. UX design practitioners and researchers should pay closer attention to the possibilities ML offers as a new *design material*. In suggesting this, our objective is to initiate an innovative research and education agenda for UX design that explores what ML might be from a design perspective.

As a first step, we chose to investigate the state of the art in UX practice. We wanted to better understand if UX designers are regularly working with ML, if they are offering ideas for what it might be, and if they are encountering problems that make ML difficult to design with. Through an online survey of fifty-one UX practitioners, we found that 63% of designers work with ML and that most work collaboratively with ML software developers and engineers. Designers working with ML expressed frustration about the difficulty of prototyping with ML, and highlighted difficulties in understanding and expressing the capabilities, limitations and potential of ML. Our findings highlight a clear need for research on new tools and techniques that make it easier for designers to ideate, sketch and prototype what new forms ML might take, and new contexts in which ML might be appropriate. In addition, this research reveals a need to develop educational resources to teach interaction designers about ML as a design material.

In this paper, we present a review of how HCI has addressed ML and its intersection with design. We describe our survey, including its design and findings. Finally, we present a series of ML related challenges for UX and interaction design, and discuss areas where new research and new curriculum might help our community unlock the power of design thinking to re-imagine what ML might be and might do.

RELATED LITERATURE

Evidence for the growing interest in the intersection of ML and UX can be seen in the number of recent articles published on the subject in popular online sources [e.g. 45]. A similar interest, in the intersection of ML and HCI, can be seen in recent CHI workshops covering the topic [23,51]. With this in mind, we undertook a review of HCI literature with particular focus on design innovation and ML. This revealed three themes: 1) technical HCI advances that improve interaction via the application of ML; 2) research to surface and address the challenges in working with "intelligent" technology; 3) work discussing challenges when designing with new or less well understood design materials. We summarize literature related to each theme below.

Technical HCI and ML

The technical side of HCI has been working with ML for many, many years to improve interaction. We do not provide a thorough review here, but instead point out several of the main capabilities and abilities this work has developed. HCI researchers have used ML to increase interaction possibilities. These range from turning people's skin into a touch interface [27] to gesture recognition [50]. They have used it to create adaptive interfaces that reduce users' efforts and automate tasks [36]. They have used ML to infer people's states, like their interruptablity [31], their routines [14], and other important contextual information [11], which can mediate computer interaction. Researchers have also used it to infer things about users. This work ranges from intelligent tutors [35] to recommenders [28] to systems that can detect things like the onset of depression [17]. Other research helped to unlock many new ways ML can improve people's interactions with technology. Our work builds on this success by probing how UX designers can apply their strength in problem reframing and opportunity finding to envision new forms for ML to take and many new ways it might deliver value to people.

The Challenges of "Intelligent" Technology

HCI has a growing body of research focused on design challenges around systems that seem "intelligent." In general, this work does not differentiate whether the underlying technology uses heuristics, more classic AI, or if it uses ML. Instead it has probed the breakdown in understanding and the many misunderstandings between users and these systems.

The challenge of integrating "intelligent" technologies into people's lives can be distilled into the automation debate between 'do it for me' and 'do it myself', or the challenge of when automation is desirable and when people want to feel in control. This debate around what makes a good user experience touches back on some of the early debates about direct manipulation and the value of users taking control vs. agents and the value of saving time and attention [49]. This is not necessarily an either/or choice, and knowledge of both is likely indispensable for a T-shaped UX designer [25,53]. Here we present an overview of HCI research that touches on this point, and on research investigating how people perceive and create expectations of intelligent systems.

HCI research into agents highlights the social nature of human-computer relationships [41], showing this is not necessarily anthropomorphic [2], but that embodiment should be based on a deep understanding of conversational function [10]. Intention recognition, effective turn taking, and effectiveness under uncertainty are deemed to be important for successful interaction [1]. As agents often have an implied, digitized or physical body, design choices like gender and ethnicity also affect the way users respond to agents. This can affect perceived task suitability [22], following stereotypical gender roles [4], influence engagement with agents [32], and affect perceived attractiveness [33]; thereby having an impact on how people perceive the intelligent system.

Intelligent systems sometimes encourage unrealistic expectations, leading to some reluctance to use them in complex or sensitive contexts [38,55]. They may inadvertently display an inability to understand the intent behind users' behavior, which results in "intelligent" features being perceived as useless and unintuitive [57]. Interaction design researchers have explored different ways systems can communicate their awareness and understanding of a user [15,58]. Research into human-robot interaction shows that physical proximity, organizational status, and task structure can alter people's experiences [34], and that expectancy setting and recovery strategies help mitigate error [37]. Also, studies of autonomous and semi-autonomous vehicles show that human behavior is highly responsive to differences in real and perceived levels of control, creating the potential for misalignment [9].

One commonality is that the majority of this work explores intelligent agents that have a presence or virtual form. This is great for services like Siri or Amazon Echo, but it does not translate to lower level services, such as search results, travel time estimators, or activity trackers, all of which work more invisibly. Another shortcoming in this body of literature is that it lacks a rich description of specific challenges of interacting with ML systems. For example, we did not see research investigating issues such as the impact of false positive and false negative responses from agents, or the need to collect ground truth labels, which might negatively impact UX.

Working with Less Well Understood Design Materials

The challenge of working with new or less well understood materials is a recurring theme in some UX research. Buxton talks about the "experience" part of user experience as a difficult material, and he notes the lack of tools that allow designers to sketch and rapidly explore a range of experiential possibilities [8]. Design value comes from instilling particular products and services with the quality of experience that sets them apart from the everyday; and without good tools, designers struggle to explore the space of possibilities.

Here, we present examples from literature in which methods and tools for exploring the experience of new technologies in use have been a key part of HCI research. Innovations range from cooperative lo-fi prototyping, in which designers work with users and technology experts to sketch out possible futures using scenarios [19], to experience prototypes where users and designers can quickly get a feel for the intended experience [7], to user enactments that offer users small sips of many possible futures [42]. Additionally, some UX research has probed the challenge of working with haptics as a design material [40]. Other work has developed sets of interactive textiles to communicate a range of possibilities designers can use in developing sensitizing concepts to support design ideation [52]. Design researchers have also discussed software as an immaterial material, noting the challenge of often needing to use developers as a prosthetic to touch the material they want to explore [43]. They have noted the challenges of working with peoples' personal data to imagine what it might be [18], and created toolkits for generating robots' social behaviors [30]. Recently, some work has explored the challenge of UX designers working with ML, and it has offered a set of mobile interaction patterns to help show designers key points where ML might add value [56].

This list is not exhaustive, but highlights some key aspects of the challenges presented by working with less well understood design materials. Again, what seems missing from this literature are methods and tools more specific to the challenges of interacting with ML systems. We saw only very limited research investigating ML specific issues like how to prototype interactions that may follow an unpredictable course.

SURVEY METHOD

We wanted to assess where the UX design community currently is in terms of ML's technology breakthrough to design innovation. In addition, we wanted to understand whether the difficulty of working with ML as a design material might be inhibiting the design response to this not so new technology. We therefor conducted a survey of professional UX design practitioners. Our intention in selecting a survey to gather data for this study was that it would allow us to quickly gain insight on the state of current practice, and to gain a broad overview of what is now emerging as a prescient area of study.

We used an iterative process to develop the survey: generating sets of questions, piloting them on ourselves and colleagues, and then making changes to address issues of ambiguity or in response to new insights that emerged after each iteration. This resulted in a nine question survey. We asked if participants worked in research or practice, if they had formal design training, if they had been exposed to machine learning as part of their design education, if they had worked on UX projects involving machine learning based services, and if yes, then to provide a short description of the project.

To understand the state of practice, we asked participants who had worked on ML projects to consider their most recent project and classify the relationship between the developers and UX team by selecting one of the following:

- The UX design team gave an interactive form to a machine learning idea that came from others (e.g. software developers or engineers)
- The UX design team generated a novel design concept utilizing machine learning, which was presented and then selected for integration into a new product or service
- The UX design team collaborated with engineers, product managers or others, and jointly developed an idea for a new product or service that utilizes machine learning

To gain insights on the types of challenges they faced when working with ML as a design material, we asked participants who had worked on ML projects to list the three biggest challenges they have faced when working with ML.

We deployed this as an online survey using SurveyMonkey. The survey was promoted via mailing lists for the Interaction Design Association, User Experience Professionals Association, and CHI. It was also listed on interaction design groups at LinkedIn and Reddit, promoted via Twitter and Facebook, and circulated to alumni of interaction design degree courses at our present and former universities. We also requested that respondents forward the survey to other UX or interaction design practitioners in their networks. All responses were anonymous. Because of the self-selecting nature of our recruitment process, we do not make strong claims with regards to how representative a sample of UX practitioners this survey represents. However, because it was widely promoted in the US, the UK and Denmark, we believe that at the very least it offers an informative snapshot of current UX practice.

The survey was available online for a period of two weeks, during which time we received fifty-one completed responses. The survey contained five multiple-choice selection questions and four questions requesting a free text response. Respondents were able to skip individual questions if they so wished. To analyze the results, we collated the responses and performed simple statistics on the quantitative data provided by the multiple-choice questions. To analyze the free text responses, each of which was typically somewhere between a couple of lines of text and a short paragraph in length, we performed a simple thematic analysis [5] to identify patterns across the data and extract key ideas. We then sought agreement across our individual interpretations. In the following section, we discuss each of the questions in turn and present the main findings from our analysis of the responses received.

FINDINGS

Thirty-nine of fifty-one respondents described their work as UX or interaction design practice in a commercial or government setting (see Table 1 for details). Of the five respondents who selected "Other", four have degrees in UX or design (see Question 2 below). They listed their jobs as product manager, user researcher, service experience designer, and experience strategy. Because our aim with this survey is to investigate the way in which ML is encountered in UX design practice rather than research, we have restricted the remainder of our analysis to these forty three respondents, i.e. the thirty nine that self-identified as professional UX practitioners and the four "others" whose self-described work practice fell within our area of interest.

Of the forty-three respondents who practice UX commercially, thirty seven (86%) reported having a degree in UX or some form of design including: interaction design, industrial design, communication design, and service design. Of these thirty-seven, only three (8%) said they had had any exposure to machine learning or machine learning concepts in school. Specific details about these concepts and courses were sketchy. One thought the subject had come up, but not as a dedicated class; one mentioned exposure to pattern recognition algorithms and the third mentioned the school they had graduated from, without giving any more information regarding specific classes.

Of the forty-three respondents that practice UX, twenty seven (63%) claimed to have worked on a project integrating ML into the UX of a commercial product or service. As Table 2 shows, respondents most commonly describe their work generating ideas for ML products or services as being *collaborative* with other professions.

Type of UX Design Work	#	Design Degree
UX or Interaction Designer working on commercial or government products and services	39	33
Interaction Design researcher working on scholarly research	3	2
HCI researcher working on scholarly research	4	2
Other	5	4

Table 1: Area of survey respondents' work

Type of Involvement	#
The **UX design team collaborated with engineers**, product managers or others, and jointly developed an idea for a new product or service that utilizes machine learning	12
The **UX design team gave an interactive form** to a machine learning idea that came from others (e.g. software developers or engineers)	8
The **UX design team generated a novel design concept** utilizing machine learning, which was presented and then selected for integration into a new product or service	7

Table 2: Involvement of UX team in generating ideas for novel ML products

Fifteen respondents were able to provide further details of the most recent projects they worked in that incorporated ML. These included recommendation engines for a variety of industries, face and object recognition for smart phone applications, agent interfaces, filtering of content for a variety of domains, intelligent media monitoring and advertising, and displaying search engine results. Respondents' involvement in these projects included: helping to define the logic, providing interaction design assistance, and providing insights about users' responses to the systems. Across these projects, respondents highlighted that they most frequently used ML to make sense of user actions. In consumer facing projects this most commonly took the form of recommendation engines, and in one case a fraud detection system. Agent interfaces were associated with decision support.

When defining ML, as they understand it, respondents listed features such as personalization, customization, prediction, and recommendation, often referring to the way that ML systems improve over time and through use, reflecting the findings from our previous question. These responses overlapped with an understanding of ML as having the capacity to learn or be trained without explicit programming and to adapt to user input or contextual change. Typical of this view, one respondent stated: "*Machine learning is the broad capability of technology systems to respond, react, and sometimes predict to users' actions and stated desires.*" Similarly, respondents described ML as having the ability to identify patterns in data and then respond to these patterns. For example, one response started: "*At a very high level, ability to identify meaningful data patterns that can surface preferences or problems and perhaps also predict future performance or outcomes.*" Respondents did not typically discuss ML with reference to any technical details, nor mention that ML techniques are rooted in statistical analysis.

When discussing how ML has made an impact on their own practice, respondents indicated that ML is seen as something that is now just beginning to be important, and which will be more important in the future. One respondent stated that: "*Applications of this capability are just starting to make their way into my projects, though it has been present as a meaningless buzzword for many years. The initial applications are very simple as machine learning is still seen as a silver bullet for all problems by laymen."* There was a general degree of excitement about the possibilities that ML might offer for UX. However, there were also concerns raised. For example, one respondent pointed out that: "*You have to be acutely aware, though, of when users start to perceive anticipation to be interference.*" Another stated that poorly performing natural language interfaces can undermine the way a system is perceived, making people think it is dumber than it really is, saying that: "*…when the machine learning (Natural Language Understanding or Natural Language Processing) is off then patients and even providers lose trust immediately."*

Challenges When Working With ML

Thirty respondents provided us with details of the three biggest challenges that UX designers face in working with ML. When we looked at their responses, several patterns emerged: first, respondents discussed challenges in envisioning what ML might be; second, they discussed challenges working with ML as a design material; third, they expressed concern in designing with ML as a "black box", raising ethical questions about the purposeful use of ML.

Difficulties in understanding ML and its capabilities

Participants uniformly described difficulties in understanding what ML was and how it worked. One respondent noted, *"We designers do not understand the limits of machine learning and what it can/can't do. Machine learning experts often complain to me that designers act like you can just sprinkle some data science onto a design and it will become automatically magical."*

Another stated that, *"It is black magic to designers. ...Designers don't understand the constraints of the technology and how to employ it appropriately."* This should not be too surprising if UX designers are only now starting to see ML transition from a buzzword to a real practice concern, and if as we see in earlier responses they did not receive directly applicable education.

Challenges with ML as a design material
Participants also mentioned challenges in working with ML as a design material. One noted, "*I think we just have yet to see its full potential in commercial products. Perhaps that's because UX/interaction designers don't know its potential…*" Another stated, *"The technical complexity is a challenge as is the need to better understand and design for that complexity. It can get deep and unfamiliar very quickly, and designers need some level of expertise to function and contribute to the work at hand.*" Inherent in these responses is the idea that designers lack a clear understanding of ML technology, and how to envision uses that don't yet exist, perhaps suggesting they need to see examples first; and perhaps consequently explaining why UX designers have not brought their expertise to bear in the use of ML in today's commercial products. This also reflects the nature of the ML projects that UX designers told us they have been involved in. In essence, these projects use ML in ways that would be totally familiar to ML researchers. Entity identification, object classification, personal recommendation, and agent interaction are classic ML topics, and the use-cases that respondents describe seemed quite typical.

In the same vein, respondents described difficulties in prototyping ML, expressing ML ideas, and noted the need for designers to collaborate with skilled technologists. One noted, *"Machine learning is hard to prototype. Machine learning requires highly skilled collaborators, when a lot of companies are only able to hire 'warm bodies'.*" Additionally, another respondent stated, *"…making interactive prototypes that incorporates machine learning is hard (haven't found a way to do that yet in an easy fashion)*," and another indicated that UX designers make statements such as *" …inputs come in …some magic happens …and all your business needs are met!*" Clearly, in order to effectively leverage ML as a design material, designers currently feel that collaborations are essential.

Challenges with the purposeful use of ML
A third frequently mentioned challenge was how to purposefully use AI and ML in systems that respondents might design. This highlighted a desire to bring a human-centered perspective to bear on ML. One respondent summarized the situation well by saying, *"While ML as an enabling technology is still in the early stages, we're likely to be one step behind the engineers that create it... changing this relationship to being one that is design-led, or at least an equal partnership will be important — we need to shift the conversation from technology to people — we'll need to bring the ethical and human centered voice to the algorithms that make it all a reality*." Another wondered who would be accountable if a system driven by ML made an error: "*If machine learning is utilized, how 'deep' does it go? If it makes a (grievous) error, who is held accountable? ....can it be trusted to make decisions or take actions on its own?*" Others talked about the necessity of holding a concern for people as a critically important value: *"Making sure it's not creepy and keeps a human element to it.*" "*…map out the right user stories and use cases, to enable effective machine learning.*"

DISCUSSION
Our goal here is to initiate a research and education agenda for the UX and interaction design communities. We have observed that ML represents an underexplored opportunity, and that for UX designers ML offers as yet unknown potential as a design material. As a first step, we culled the literature for evidence of the overlap of ML and interaction design. We also surveyed UX design practitioners about their experiences working with ML.

Limitations of the Survey
Inevitably, the richness and depth of the data gathered through surveys is limited in comparison to that we may have gained from interviewing UX designers. Our intention here is to first gain a broad overview before digging in to investigate the particular concerns of a small selection of designers. Our hope with this survey is to lay a foundation that will enable other researchers to pick up this research thread and investigate the challenges associated with working with ML as a design material.

Our survey only reached a small number of UX practitioners; however, it had a broad geographical spread of respondents. We promoted the survey widely throughout networks in the US, UK and Scandinavia, and we targeted UX designers for whom ML is a current or foreseeable topic of concern. We believe that this offers a diversity and representativeness that may not have been present had it been slightly larger but more geographically restricted.

Key Findings From the Survey
Drawing collectively from our literature review, our investigation on the state of the art in UX and ML, and our survey responses, we present other key findings:

First, it is clear that the UX design community understands ML broadly, but not specifically. Nearly two decades of research covered in our literature review revealed generalizations about this technology, but few specifics about what is needed to design with it. This finding was echoed in the survey of UX professionals, in the descriptions of what ML means and how it impacts designers' work. Answers were in broad brushstrokes rather than detailed answers with specific examples. Similarly, when respondents discussed the challenges ML presents, a difficulty in understanding ML was repeatedly highlighted. The difficulties expressed in understanding and therefore ideating and innovating with ML is a clear challenge for designers. However, the literature also points to examples where the development of effective tools and techniques has released the potential for better, more sophisticated design with other complex technologies. We can only imagine that the same will happen for ML in the next decade.

Second, we believe that current interaction design, UX, and even HCI design education cannot prepare the next generation of design graduates to incorporate ML into their work. This is evidenced by the finding that only three respondents had taken a class that they considered had taught them how to integrate ML into the UX design of products and services. Moreover, of the three that did respond positively to this question none provided particular details regarding the class in question. It is further evidenced by the absence of this topic from major UX and interaction design course textbooks [e.g. 13,46]. Finally, the stated difficulties that practicing designers express with regards to understanding and communicating ML suggests they have not been sufficiently prepared in this regard.

Third, while ML clearly pushes the boundaries of design, the balance of collaboration with engineers and software developers is currently such that design-led innovation is still rare. We find evidence for this when we look at designers' descriptions of how the ML projects they have been involved in unfolded. Only 25% of these were classified as the UX design team leading the generation of a novel design concept. It is also evidenced in the challenges respondents described. The technical complexity of ML is a theme that was repeated, as was the need for collaborative expertise.

Finally, our collective research efforts showed that prototyping with ML is difficult. In the era of industrial and product design, designers created prototypes in the form of sketches, plans, and physical models made of paper, cardboard, or foam [26]. The era of UX design added skills from storytelling, narrative, and film to the prototyping process. Designers relied on stories, film techniques, digital video, and stagecraft to construct situations where experiences could be evaluated, particularly with products that do not yet exist [7,42,59].

ML clearly demands a new type of prototyping, one that does not yet exist. We believe that there are a number of reasons for this. First, "learning" implies that the system and data will change over time. Designers are not accustomed to designing a form for data that is dynamic at a large scale. Second, the way in which ML and designers treat data is quite different from each other. Designers mostly visualize data and look for correlations and patterns that "make sense;" that fit with their understanding of how the world should and does work. ML in contrast finds machine-recognizable correlations and patterns in data. It applies no common sense; thus correlations can appear simplistic and even stupid to a person trying to make sense of the patterns. These two efforts are often at odds. Finally, a prototype that relies on ML data will most likely be inordinately complex, and may have many possibilities and a high degree of uncertainty. It may also require an unwieldy amount of ML data to create a functional prototype. This challenges the general idea of prototyping; of making just enough of a system to assess if this is the right direction to go. ML seems to require a much higher level of commitment; perhaps conflicting with UX mantras like "fail fast, fail often."

Challenges for UX Design

The survey results showed that ML is considered to be technically complex and challenging. It was also described as having ethical implications, being potentially expensive, and largely falling outside the scope of smaller projects. Respondents described difficulties in understanding and therefore expressing the capabilities, limitations and potential of ML within a UX design context. They considered interactions with ML difficult to prototype because such interactions are dynamic, and their outcomes are potentially unpredictable. This creates a risk that users might be prevented from achieving the things they want or need to do. They also identified potential difficulties in gathering enough user data for successful ML, and in drawing useful insights from these data. Respondents believed that mental models of ML are often poor, and highlighted a need for good user research to provide a human-centered focus and ensure ML is incorporated in a thoughtful way, rather than interfering or being "creepy". Education, experience and training do not currently prepare designers for working with ML, and they highlighted the potential benefits of working with skilled technologists, engineers and programmers.

These findings have led us to consider some initial challenges for UX design research and education, with regards to working with ML as a design material. We don't suggest that this is an exhaustive list of the challenges that designers face when working with ML, nor even that these will end up being considered the most critical challenges. This is instead an *initial* list of challenges. The motivation for each of these challenges is well grounded in our research data, and we believe they form a solid starting ground. We therefore challenge ourselves, and our community, to investigate how we might:

- Consider the interplay between ML statistical intelligence and human common sense intelligence
- Envision opportunities to apply ML in less obvious ways
- Represent ML's dependency on data in early prototypes
- Foreground ethical considerations of ML

Consider the Interplay of ML and Human Intelligences

Our survey indicated that prototyping with ML presents a significant challenge for UX designers. One reason respondents stated for this is that interactions with ML systems can seem unpredictable, and therefore be difficult to clearly express. It is hard to effectively imagine what the experience will be, or the likely performance errors, until the system is built; therefore making it difficult to assess potential value versus "creepiness". The statistical intelligence displayed by ML may result in a very different interpretation of the same data than common sense human intelligence. This can make performance errors seem bizarre and hard to explain, resulting in potentially dissonant user experiences. To mitigate this, UX designers should consider interactions not only from the more familiar human perspective, but also the perspective of statistical inference, and crucially how these two perspectives might interact. We invite UX and interaction design researchers to build on the examples outlined in our literature [e.g. 15,30], and develop tools and techniques for considering this interplay. So that, for example, we might better anticipate, mitigate or account for ML statistical errors, such as false positives or negatives, or design for perceptive qualities. One area where this may play out is in ML based agents, such as those found in virtual assistants like Amazon Echo and Google Home. Currently, these require somewhat awkward voice commands to initiate interactions. However, the perceptual awareness explored in [15] points in a direction that designers might explore to fundamentally reassess the UX qualities such products aspire to.

Envision Opportunities to Apply ML In Less Obvious Ways

Our survey data indicates that identifying opportunities to apply ML in novel and interesting ways, that respond to emerging trends and uncover unforeseen desires, is currently challenging for designers. Identifying and ideating around these opportunities is a key aspect of the design-led innovation that is apparently common elsewhere, and yet currently missing for systems designed with ML. This is likely because designers' understanding of ML is at a relatively broad-brush scale, making it difficult to ideate, sketch and elegantly prototype ML concepts. We hope that UX and interaction design researchers can build on the examples in our literature review [e.g.7,42] and develop tools and techniques that help envision how ML can be applied in less obvious ways.

An example of applying ML in a less obvious way might be to reevaluate how recommender systems, such as those used in ecommerce or media platforms, are conceived. These represent one of the most familiar forms ML takes, and one that has remained largely unchanged for the last two decades. Most recommenders rank items in order to narrow the apparent choices to a subset of those most likely to result in user selection. The UX design associated with these is an add-on, an afterthought to the classification capabilities of the underlying algorithms. A design-led innovation in recommender systems might overturn this and start from the experiences of the most enthusiastic collectors of books, music or film. It might consider pleasure in the effort of discovery, and the knowledge gained along the way. Designers might explore what makes these search efforts meaningful; and how to enable a more nuanced view of the way in which different individuals' tastes develop, and how they differ from or intersect with the crowd. This design-led exploration might also find ways to mitigate the dissonance caused by inappropriate suggestions, which currently remain all too familiar. The challenge for researchers is not only to undertake such reimagining but also to develop the tools that allow us to explore the results with potential users.

Represent ML's Dependency on Data in Early Prototypes

Our survey data indicates that UX designers may not clearly understand the dependent relationship ML has with data and ground truth. This is also the impression gained from a series of online UX articles that were part of our literature review, and in which designers and commentators treat ML as if it were some type of magic. We therefore challenge UX designers to be more open about the difficulties in planning for data gathering and labeling, like [56], and to develop tools and techniques for prototyping the interdependencies between data and UX early-on when working with ML

Foreground Ethical Considerations

Our survey found that one of the main challenges identified by UX designers with regards to ML is to consider its ethical implications. These responses fit in with a long tradition in design of the concern of the designer in creating something that is ethical, purposeful, and pragmatic [e.g. 39,44], but also in computer science traditions [e.g. 3]. Our hope is that the UX and interaction design communities continue to contribute to this conversation by keeping the needs and desires of people at the forefront of everything that they design.

CONCLUSION

Machine learning (ML) is now a fairly established technology, and user experience (UX) designers have begun to integrate ML services into the things that they design. This paper presents a survey conducted with current UX practitioners to understand how well ML is understood and operationalized in design practice. Our findings show that the design community is only beginning to understand this technology and its application. We expand on these findings to present a series of challenges for UX and interaction design research and education.

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