

Sketching Machine-learning-mediated UX

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Abstract

Machine learning (ML) applications *that directly interface with everyday users* are now increasingly pervasive and powerful. However, user experience (UX) practitioners are lagging behind in leveraging this increasing common technology. ML is not yet a standard part of UX design practice, in either design patterns, prototyping tools, or education. This paper is a reflection on my experience designing ML-mediated UX. I illustrate the role UX practice can play in making machine intelligence in the wild usable and valuable for everyday users: it can help identify 1) how to choose the right ML applications 2) how to design the ML right. The conception is a first step to untangling the tight interplay between ML and UX. I highlight the unique challenges and the implications for future research directions.

Introduction

Machine learning (ML) applications *that directly interface with everyday users* are now increasingly powerful, diverse and pervasive. The maturity and prevalence of this technology catalyzed the notion of *ML is the new UX*, that is ML will be the most important way to improve user experience (UX), and ultimately would *be* the new user interface (Brownlee 2015; Kuang 2013; Yang, Zimmerman, Steinfeld, and Tomasic 2016).

However, designers are lagging behind in leveraging this not-so-new technology. The shape of the ML-mediated future seems have been mostly driven by data availability and learner performance rather than a deliberate vision. ML has not yet become a standard part of UX design practice, in either of design patterns, prototyping tools, or design education. UX designers do not have enough tacit understanding of ML to operationalize interaction flows that proactively adapt or evolve over time (Yang, Zimmerman, Steinfeld, and Tomasic 2016).

How should UX design practice utilize and instantiate ML? How does UX incorporate and negotiate the uncertainty, temporality, and under-interpretation of ML algorithms? How can practitioners tailor machine intelligence

for user needs and adequately weave them into real-world contexts?

These fundamental UX questions underlie my research in HCI. Over the past 3 years as a researcher at Carnegie Mellon University, I have concentrated on designing intelligent systems for real world uses. In particular, my research involves 1) designing a ML-driven software that helps clinicians with patient selection for artificial heart implant surgeries (Yang, Zimmerman, Steinfeld, Carey, et al. 2016; Yang, Zimmerman, and Steinfeld 2015); 2) adding intelligent UI adaptations to a mobile app for users with disabilities (Yang, Zimmerman, Steinfeld, and Tomasic 2016), and 3) designing autonomous driving UX. These systems interact with end users directly in high-consequence real-world scenarios, where user perception and experience of ML are vital to their success.

In this position paper, I reflect on my experience designing these systems, then map the roles UX should play in making machine intelligence usable and valuable *in the wild* for *everyday users*. I highlight the unique challenges designing ML-mediated UX entails, as well as implications for future research pathways.

Case Study: Designing ML-driven Clinical Decision Support

One of my ongoing research projects is designing an ML system that aids high-risk clinical decision-making. This software that helps medical professionals decide whether and when to implant an artificial heart into an end-stage heart failure patient (Yang, Zimmerman, Steinfeld, Carey, et al. 2016; Yang et al. 2015). Previously, such systems take a context-less, prototypic form: A list of patient condition measures is fed in and produces an individualized prediction of patient trajectories, such as likely survival and other post-surgical risks (Bellazzi and Zupan 2008). Interestingly, almost all these systems have failed when moving into clinical practice, despite their effectiveness in labs (Yang et al. 2015).

In order to better understand the system's application in a real world environment, we performed a field study with current clinicians. We interviewed and observed clinicians

caring for VAD patients at three different implant centers for 13 days. Our field study identified several barriers that could negatively impact the use and perceived value of machine intelligence, such as an attitudinal barrier. Physicians perceived no need for data support because they felt that they know how to effectively factor patient conditions into clinical decisions. They also lack trust in the ability of machine intelligence; instead, they rely on professional networks for actionable suggestions.

These observations in the field forced us to confront two fundamental questions (Borrowing from the vocabulary of Schön and DeSanctis (1986)):

- 1) What is the right thing to build? (“problem-setting”) To overcome the attitudinal barriers, we should design machine intelligence to skill clinicians rather than de-skilling them, to *make them feel better with their decision making*, rather than making the decisions for them;
- 2) How do we build this? (“problem-solving”) By sketching service blueprints, we identified appropriate situations where ML could be helpful. This critically reshaped the form decision supports take to better fit into day-to-day clinical practice and workplace culture (Yang, Zimmerman, Steinfeld, Carey, et al. 2016).

This case study exemplifies interdependencies inherent in the design of ML-mediated UX: ML and UX exist in a symbiotic relationship to one another. UX needs the context awareness and personalizability enabled by ML; ML is also dependent upon UX design to be perceivably valuable and useful to the users.

Recently, many researchers started to investigating human components of ML. However, there still is a lack of systematic understanding that is pertinent to *UX practitioners* and apposite to ML systems *in the wild* (as oppose to the interactive machine learning works for developers (Patel 2010), artists (Fiebrink, Cook, and Trueman 2011), makers, or end users in lab settings (Amershi 2011, 2012)).

Below I propose two fundamental dimensions along which to begin a discussion on the roles UX should play when working with ML as a design material: learning the right thing and making the learning right.

UX’s Role in Learning the Right Thing

“To be design-oriented (in HCI) is to consciously seek to intervene and manipulate, aiming to convert an undesired situation into a desirable one.” (Fallman 2003)

UX Goals Converses with ML Goals

The moto of UX, “the desired future”, is at the center of HCI design. Early investment in activities like user studies

help designers ideate on divergent framing and solutions, and establish *what is the “right thing” to design*.

In contrast, machine learning efforts emphasize *what can be (accurately) learned* given the available datasets over a designated application. The shape of the ML-mediated future seems have been mostly driven by data availability and learner performance rather than a deliberate vision. The above case study exemplifies this inherent mismatch. Consequently, many existing ML systems fail to account for the users, or to fit into its context at large (Amershi et al. 2015; Yang, Zimmerman, Steinfeld, Carey, et al. 2016).

I promote the idea that UX of ML should be planned early in the system development process, *with goals explicitly articulated and thoughtfully seeded* (Yang, Zimmerman, Steinfeld, and Tomasic 2016). I list several common lenses through which ML goals are defined. This list is by no means meant to be complete; it is, however, meant to be useful to dissect UX consequences of machine intelligence. ML systems in the wild often need to cover and balance two or more facets. (e.g. Rader and Gray 2015)

- From *users’* lens. For example, our design of the decision support tool has the explicit goal of helping clinicians feel they are doing better work, and not necessarily automating the part of work that makes them feel like an expert.
- From *service providers’* lens. For example, recommender systems often aim for longer use sessions and more user engagement.
- From a *humanistic* lens. This perspective of design goals addresses ML consequences at large. For example, how do media content rankers minimize the filter bubble effect (Nguyen et al. 2014)? How can designers prevent “scoring” algorithms— systems that score teachers and students, sort resumes, grant or deny loans—manifest pernicious feedback loops that enforce biases? (O’Neil 2016; Rader and Gray 2015)

UX Identifies New ML Opportunities

UX design approaches have great potential in identifying new ML opportunities, because design in early phases is exploration. This means UX professionals often invest time on divergent work, essentially looking around in a design space of possibilities.

Designers can situate ML algorithms in different contexts and for different audiences. UX professionals routinely consider user needs and desires, working to embody the people they made technologies for (Zimmerman, Forlizzi, and Evenson 2007). For example, in the decision support tool case, our field study revealed rich details illustrating the clinical workflow and workplace culture, which be-

came material for designing an effective decision support system.

With adequate ML literacy, designer can even potentially invent new ways of utilizing data, envisioning and operationalizing ML methods.

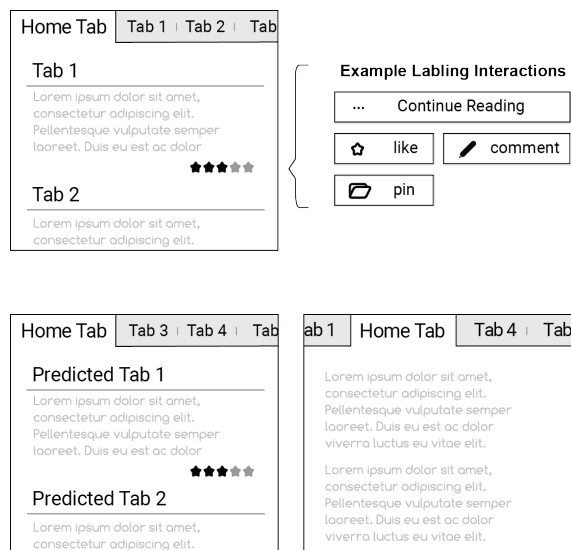
More work needs to be done to enable UX practitioners to leverage ML as a design material. UX education and toolkits must provide new means that help UX teams develop a tacit understanding of ML -- that is not simply teaching how ML works, but empowering them with *enough* technical literacy to be able to 1) *ideate creatively yet practically*, and 2) to better collaborate with machine learning experts.

UX's Role in Getting the Learning Right

UX Manifests the ML Pipeline

ML-mediated interfaces simultaneously shape user behaviors and drive its underlying machine learning pipelines, raising exciting new challenges and opportunities for designers.

When dealing with these interfaces, UX teams should consider what aspects of user behavior and context to capture in order to accurately externalize and interpret the interaction traces logged. They also need to consider how to detect inference errors and even capture labels to enable reinforcement learning. Ideally, *UX professionals construct interfaces in such a way that the traces of user interactions can serve as a ready source for machine learning.*



Stage1. Interfaces with No Adaptation

2. Low-confidence Adaptation 3. Full Automation

Figure 1. An Example of Adaptive UI Design Patterns - Landing Tab. On this set of interfaces, the data traces of user interactions

can serve as a ready source for machine learning. (Yang, Zimmerman, Steinfeld, and Tomasic 2016)

This vision marks an exciting space for future design research in HCI. My previous work seeks solutions to this challenge in design patterns and prototyping toolkits (Figure 1, (Yang, Zimmerman, Steinfeld, and Tomasic 2016)). Others address this challenge by developing the ML system and interfaces simultaneously (e.g. (Zimmerman, Tomasic, et al. 2007)), or creating an entertaining dialog that motivates users to contribute information that can be used as labels for personalization (e.g. (Wood 2014)).

UX Choreographs User and System Evolvement

A design that satisfies all the identified data requirements does not guarantee pleasant user experiences. In fact, creating interaction flows with two dynamic parts (users and the machine interfaces) entail many new design challenges.

UX Evolvement Over Time

ML's ability to evolve UX over time opens up exciting design opportunities for interaction and service designers. For example, data-driven personalization can serve as an important part of building and maintaining long-term customer relationships with a view toward creating lifetime value.

However, promises of future intelligent interactions often come at the expense of usability at the moment. In order to make confident inferences, ML systems often need more explicit input from users. Facing a new user, how can the interaction design *induce more interactions*, in order to collect high-quality ML features and labels? Facing a user with rich use history and context data, how can a designer find the harmony between automation and user engagement?

Appropriating UX for ML Performance

Kay, Patel, and Kientz (2015) raised the question of "how good is an 85%-accuracy classifier?", addressing the subjectivity of ML performances. The answer to this question comes down to the tradeoff between the quality of the learning system and the risk/reward users associate with a successful or failed prediction. Designers should consider the potential benefits and costs of UX at each stage of the interface evolvement, and accordingly set an estimated accuracy threshold required for triggering the next level of personalization or automation.

Discussion

This paper elaborated on two fundamental roles UX practice play when designing ML-driven systems. I argue that, as with most of the other emerging technologies, designing ML-mediated UX should emphasize balancing the back-end concern of ML performance and usability (getting the

thing right) with an up-front investment in exploration and ideation (getting the right thing).

Like others in the HCI and UX communities, I promote the idea that ML is the new UX. I envision UX practitioners leveraging machine learning (ML) as a design material *creatively* and *thoughtfully*, guiding users and technologists toward a deliberative ML-mediated future.

More work needs to be done to advance current UX practices toward this vision. I will continue to work on growing an understanding of and supporting the conversation between ML and UX teams. With these two fields working in concert, design goals can become grounded situations for future ML work, while ML methods can be appropriately applied to UX problems. I encourage the UX and HCI research community to join us in investigating new ways to evaluate the UX benefits and risk of ML and developing new ML capable sketching and prototyping tools.

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