Making Machine Learning Accessible to All: A Position Statement

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Abstract

In my research I help make machine learning accessible to all, enabling people better "teach" and use learning algorithms in real-world contexts. In my practice, I design user experiences for multiple high-consequence interactive machine learning applications: from data-driven clinical decision support systems, to context-aware mobile services, to autonomous cars. Reflecting on this related vein of practice and research, I distill ML technical knowledge and ML thinking into design methodologies, patterns and prototyping toolkits that enable more people to better ideate feasible, meaningful and creative forms and functions of machine learning technologies. In this position paper, I describe two lines of my inquiry that move us towards the vision of "ML for everyone".

Preferred format: Presentation.

My Position

Machine learning (ML) promises powerful insights and solutions for a wide variety of domains. It can improve the lives of people from all walks of life. However, crafting these solutions generally requires knowledge only a few people possess. One way to overcome this bottleneck is lowering the barrier for creating ML and enabling more people to build ML solutions for their own purposes and areas of expertise. Democratizing ML will empower new and innovative uses for ML. It can help mitigate algorithm biases and related issues encompassing machine intelligence today. Some in the tech industry have begun promoting the idea of "ML for everyone".

In my work, I aim to make ML accessible to technology designers and domain experts through the lens of Human-Computer Interaction (HCI) - that is, a discourse centered on how to help people better "teach" and use learning algorithms, rather than how to enable the algorithms to learn better. To do so, I pursue two high-level research thrusts. First, I construct empirical models of peoples intuitions towards ML and particularly as they relate to building ML models for their own purposes. Second, I construct novel toolkits and machine teaching systems that better match peoples purposes and understandings.

Machine Learning for Designers

My thesis work focuses on technology designers; one emblematic population among non-ML experts who also reshape ML techniques into how the world interacts with machine intelligence every day. Enabling designers to perceive and envision ML in creative and thoughtful ways not only informs research on making ML accessible, but promises shorten the distance between technical advances in labs and real-world product innovations, between research and practice. However, designing ML-enhanced user experiences (UX) remains challenging. Today, thinking of what ML might do is not a part of the UX design practice. Designer have no design patterns nor do they have prototyping tools that support thinking and sketching around ML advances. UX design education programs and practitioner-focused UX books never mention ML. Because of this, today, designers fail to recognize opportunities to utilize ML in their designs, and they rarely conceive of new ways to use ML (Yang et al. 2016b; Dove et al. 2017).

My work is drawing out design patterns that help designers recognize some of the most obvious places to use ML to enhance UX and it is working on new prototyping tools that can help designers investigate and document how an adaptive system unfolds as it learns. Reflecting on my own experience of adding context-awareness into mobile applications, I along with my collaborators developed a set of ML-friendly user interface (UI) patterns and boundary objects (Yang et al. 2016b). Following the design patterns, the traces of user interactions on the interfaces can serve as a ready source of training data for initial and reinforcement learning. The new boundary object is crafted specifically for envisioning and communicating interaction flows that proactively adapt or evolve over time, and for pushing designers to consider and articulate UX benefits and costs of a successful or unsuccessful adaptation. The patterns and the boundary object together can scaffold an effective conversation between designers and data scientists.

Beyond instrumental design patterns, my work aims to enable designers to envision new forms of ML that have not been imagined by the data scientists who focus on making the technology work; namely "ML as a design material". Currently, little is known about how to enable designers to more effectively envision new forms for ML products and services. In formative work, I mined HCI literature and mapped the design space of technical advances that use ML as starting places for design envision. I interviewed UX designers working at tech companies who regularly create new services that employ ML to understand how they work differently than other UX designers. I documented how they have synthesized their design process, invented hybrid design methods and their collaboration with ML professionals. I hosted many ML design workshops with UX design students at Carnegie Mellon University and Savannah College of Art and Design. At these workshops, the student designers tried a variety of tools to help them more effectively envision new products and services that use ML. Collectively, this work has reveal many challenges and opportunities for transforming ML into an effective design material.

This work has produced three main findings. First, designers decouple the basic veracity of ML algorithms from their validity in the context of use. Veracity is a matter of technical world or data science; validity is a problem of broader cultural acceptance or appeal. Second, ML as a design material exists as part of a design intention. ML in the context of UX design resists easy assimilation into a complete or fixed taxonomy of descriptive mechanisms, such as supervised or unsupervised learning. **ML application is wedded to or arise from the users holistic experience. ML is betwixt and between.** Third, **you cannot make ML accessible to designers by teaching them how ML works**. Instead, we must create new ways for sensitizing UX designers with ML capabilities and limitations; we must create new methods and boundary objects to help them collaborate with data scientist and establish a shared problem framing along with a shared space for alternatives.

As one of the few researchers addressing this problem, this work has spawned a burgeoning field of research within HCI: ML as a design material. I presented this work to industry including to teams of data scientists and software engineers. I am finding allies among both designers and engineers, both in AI-savvy enterprises and startups. By staying highly relevant to the ML technical advances and maintaining a designerly lens, my work unfolds in unfamiliar, unconventional directions, forcing new terms into the world of ML research.

Machine Learning for Domain Experts

Motivated Domain Experts

The second thread of my work focuses on making ML accessible to intermediate machine "teachers" domain experts who are not formally trained in ML, and are actively "teaching" learning algorithms to solve the particular problems of their interest. Thanks to the many novice-facing ML tools such as Weka, many potential teachers have been experimenting with ML in a sizable scale. Interestingly, little is known about who they are or how they work to teach. In the ML literature, there seems to be a dichotomy between ML professionals and amateurs who are passively engaged in the ML pipeline as "human oracles".

To help more people engage with ML, we must first understand these users. Recently, I conducted an ethnographic field study to teachers, empirically synthesize peoples understanding of how ML works, and their strategies for constructing and improving a learning model. I found a real need to re-frame the roles domain experts play. Most subject domain experts I interviewed apply themselves to a wide range of practical learning tasks and in doing so, they perceive no problems with building working ML models. I observed that through the process of interactive ML, domain experts project trust in the self-made algorithms much more than ML experts. This provokes us to hypothesize critical value for machine teaching interactions in enhancing human trust in ML. At a higher level, I demonstrated that **amateur machine teaching has its unique value and advantage**; a radically different mentality for traditional designs of crowd-sourced and end-user ML systems.

Informed by the non-expert ML mental model, I invented a radically different machine teaching experience design: Test-driven Machine Teaching. As a novel framework, it intends to inform and inspire researchers in designing iML tools for non-ML experts.

Taking inspiration from Test-driven development, test-driven machine teaching employs user-identified test cases serve as the major interface and language between machine teachers and learners. The test cases skirt non-experts lack of understanding of MLs internal mechanisms, yet surfaces model errors and prevents teachers from overly trusting percentage accuracy as a sole performance measure. In comparison to statistics and visualizations, hand-picked test cases also provide non-experts more concrete, direct probes into the data and the model performance. Moreover, the process of eliciting test cases surfaces teachers priorities and expectations towards the learning algorithm, offering opportunities for tailored in-situ teaching supports. We imagine prior ML research on boosting teacher performance and efficiency could be leveraged in support of this. I see iML tools as central artifacts as a perfect fusion point of the previously parallel efforts in the fields of ML and HCI in making ML accessible.

Less-Motivated Domain Experts

Clinical data mining is a canonical case in end-user ML research: Doctors and clinicians utilize their domain expertise in building ML models in the form of decision support tools (DSTs), leveraging machine intelligence in improving healthcare quality. My research, however, found that this is unlikely to happen. In collaboration with several hospitals across the US, I dove into real clinical practices to understand ML applications real-world complexities and contexts. They commonly perceive no need for decision support, and lack trust in the ability of ML to help. Further, the hierarchical but collaborative clinical culture naturally stratified across decision makers and computer users (Yang et al. 2016a).

The key takeaway from this formative study is that technology developers should not assume clinicians feel that they need help. And when they dont feel the need for help, they will not walk up to the system and seek advice for the decision. Instead, to realize their true value in such collaborative, high consequence situations, ML systems should make clinicians feel they are becoming better at their job (rather than doing the job for them). These systems should enhance clinical decision quality by leveraging advantages of both human and machine intelligence. The systems also need to integrate and even leverage the social context in order to place the information in front of real decision makers.

As one of the first designers pushing ML into healthcare, I deeply understand why ML systems have almost always failed in clinical practice. To enable ML not only to achieve high performance in labs but deliver value in the real world, I reflect on my research on ML as a design material, and on laypeoples intuitive understanding of ML; I have since been inventing new forms and functions of DSTs that are radically different from existing. On one hand, I embedded ML prognosis into presentation tools that clinicians use at major touchpoints within clinical practice. The DST I am working on can automate the tedious information retrieval tasks, and ease its recommendations into the discussion materials that the whole clinician team reviews. On the other hand, I work with statisticians and clinical professionals in developing ML systems the physicians exhibit a need for decision support, such as monitoring to make sure a patient does not arrive at an implant facility after it is already too late for an implant. In near future, I will continue to improve and evaluate a suite of these ML systems.

Closing Note

The past three years of my research has been helping technology designers and domain experts to grasp and temper ML in creative and utilitarian ways, lowering the barrier for them to understand, build, and utilize ML solutions. I have designed radically new iML tools and ML applications that embrace non-experts' purposes, mentalities, and real-world contexts. As I look forward, I intend to use the expertise I have developed over this breadth of work to move us towards the vision of "ML for everyone". I encourage fellow HCI/Design researchers to join to realize the true potential of ML.

Bio

Qian Yang is a Ph.D. student at Carnegie Mellon University Human-Computer Interaction Institute. She is advised by John Zimmerman and Aaron Steinfeld. Her research interests include *machine learning as a design material* and creative design of machine learning systems. She earned an M.Des, a B.S and a B.BA from Shanghai Jiao Tong University. Contact her at yangqian at cmu dot edu or visit yang-qian.github.io.

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