Bridging Machine Learning and Real World Complexities with Interaction Design

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Abstract
Many machine-learning-powered systems struggle to deliver its value in the real world, despite compelling evidences of effectiveness in lab studies. The challenges lie not in technical performances, but likely in the lack of understanding of and design solutions to its rich and complex contexts of use. My work addresses this challenge with interaction design approaches.

In this position paper, I share two major parts of my design research: 1) designing a prognostic tool supporting high-risk clinical decisions in real practices, 2) designing machine-learning-ready mobile app interfaces. Both of them include my insights in how to better position machine learning in its context with radical and programmatic near-future solutions respectively.

Author Keywords
Interaction Design; Design Research; Machine Learning; Adaptive user interface; Decision-support Tools.

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

Challenges for an Intelligent Clinical Decision-support System:

Attitudinal barrier: Clinicians perceive no need for decision support. They trust their expertise and experiences more.

Social barrier: In the highly hierarchical workplace, a team of mid-levels support senior physicians' decisions.

Need barrier: At the input end, machine-learning systems take in quantitative and explicit inputs, while challenging decisions are often characterized by unavailable or ambiguous medical/social evidence;

Environmental barrier: No clinical decisions happen in front of a computer. Clinicians are constantly moving. They wash hands more than 60 times in 3 hours during ward visits, making computer use a hassle.

Introduction

In an era when machine-learning-improved software is increasingly sophisticated and pervasive, we interaction designers, surprisingly, found ourselves lack guidance on how to design these systems. There are no established patterns to guide design of machine learning-powered systems; design tools and workflows have no mention of machine learning considerations; the design research community has produced limited insights on users and use contexts of these systems.

My work has been devoted to expand the scope of and reframe the role of this new technology, and find interaction design solutions to address above issues. In this position paper, I share two major parts of my design research: 1) designing a prognostic tool supporting high-risk clinical decisions in real practices, 2) designing machine-learning-improved mobile app interfaces.

Design real-world-ready ML systems

I am designing a prognostic system for high-risk clinical decision-making. In the last 30 years, almost all of such systems deployed failed when moving into clinical practice, despite compelling evidences of effectiveness in lab studies. The challenges lie not in technical performances, but primarily in a lack of user-centered HCI consideration[3].

To advance on this challenge, I conducted a month-long field study in 2015 summer investigating how clinicians make a heart pump implant decision (full paper to be presented at CHI16'). My study revealed many barriers a data-powered intelligent system has to overcome, namely, attitudinal barriers, social barriers, need barriers, and environmental barriers.

These barriers challenge the assumed mindset of how machine-learning system works (at the point of decision-making, the system takes in a list of variables and produces a prediction) and force us designers to deeply reflect on the role data science play in decision-making. There is a real need to understand the machine learning systems in its richness of context particularly 1) to tailor the systems to how the decisions are actually made, and how the decision-makers want to be supported; 2) to seek out new forms of interactions that make them feel they are becoming better at their job, rather than being replaced by technology, through their interactions with technology; 3) to explore new roles machine learning systems should in its social context, i.e. Enriching and facilitating the relations among a group of decision makers as a decision support.

Design ML-ready interfaces

In the above project I employ context-focused design research approaches to propose radical reformations of machine learning system design. My other part of research explores pragmatic IxD practices to enable "learning in the wild", that is machine learning directly from use of the interfaces. I addressed the need to develop the machine-learning system and the interface simultaneously, allowing negotiation between the input requirements of the learning system and the actions required by the user to complete the work [4].

Today machine learning (ML) has become one of the most attractive and effective tools for mobile UI/UX designers. The idea of improving UI with ML is not new, and the HCI research community has done great work to demonstrate this functionality. Some in the

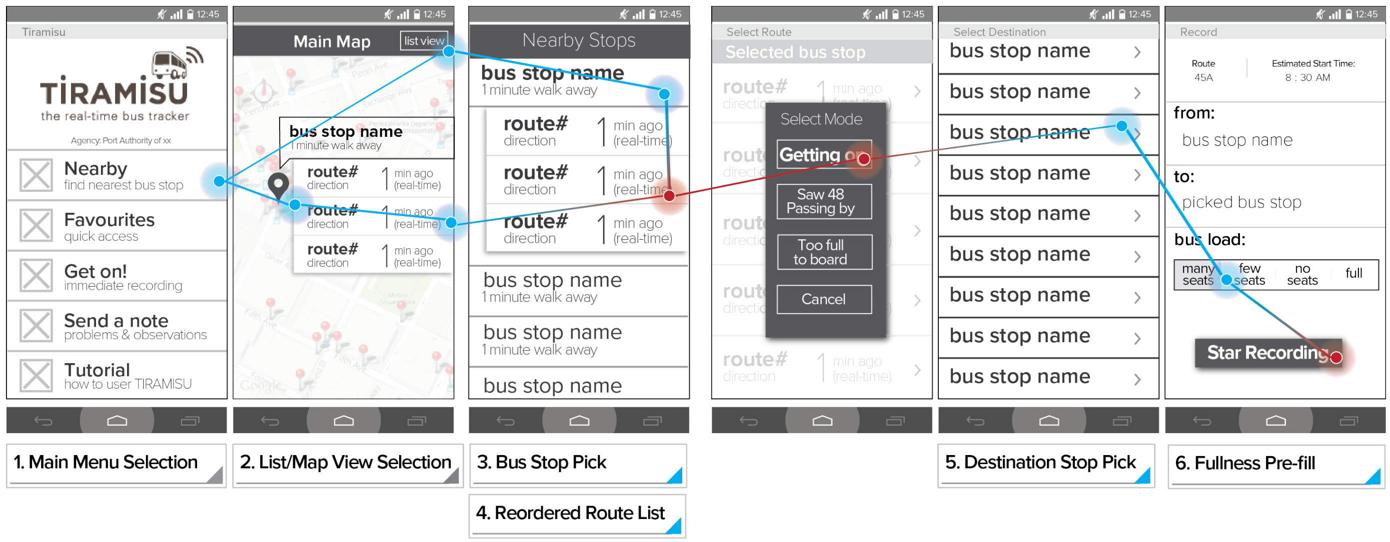

Figure 1: Exemplar IxD deliverables with annotations of machine learning opportunities. This improved format of wireframe can help designers recognize possible automations in the interaction flow, encourages them to weigh its costs (penalty of user taps and navigation efforts when the prediction is wrong) and benefits (saved user efforts when the prediction is accurate). It is also meant to serve as a boundary object to support their conversations with UI developers and data scientists.

interaction design practice community even claim that: *AI is the new UI*.[1,2]

> *Most people make the mistake of thinking design is what it looks like. Design is how it works. As our screens get smaller and fade away, ultimately, it would be AI, not UI, that would win the war.*[1]

If AI really is the new UI, and if mobile apps will be routinely adaptive, it seems interaction designers should be noting the adaptation opportunities when designing. Interestingly, this is not currently a part of most interaction design processes. In reflecting on my own experience in adding machine learning to IxD, I argue that making machine learning an afterthought is fundamentally problematic. Concretely, the traces of the interaction flow do not provide a ready source of data for machine learning systems, and the non-adaptive interfaces presumed accurate information, leaving little flexibility for users to correct inaccurate prediction.

My undergoing research focuses on this neglected space between IxD design practice and machine learning, reaching for a better reciprocity between the two. I create UI design patterns that help designers recognize and prepare for machine learning opportunities; I also propose improved wireframe deliverable (Figure 1) that could serve as a boundary object to converse to and closely collaborate with UI developers and data scientists.

Discussion

The examples above show how I design a better positioning of machine learning in its context, with radical and programmatic near-future solutions respectively. My future work includes envisioning radical design solutions for real-world-ready machine learning systems as well as development of pragmatic prototyping tools for intelligent UI designers. I look forward to exchanging ideas and experiences with other workshop participants.

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