The Relationship Between User Experience and Machine Learning

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Abstract
Based on our primary research question of what the relationship between user experience (UX) and machine learning (ML) is, this literature review examines how UX and ML function independently and interact with each other. We review literature with regard to the development of UX and ML separately, as well as the combination of these two areas. Our ultimate findings focus on four dimensions: the relationship between UX and ML, the advantages of integrating UX and ML, the challenges of applying ML technology to UX design, as well as the future implications in using ML to enhance UX. Finally, we give our suggestions concerning the establishment of a better ecosystem between UX and ML.
Keywords: machine learning; user experience

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1 Introduction

User experience and machine learning are two relatively young fields that have progressed individually over the past couple decades. The disciplines offer ample research opportunities because they are becoming increasingly relevant and widely implemented across industries and applications. User experience (UX), within the field of human-computer interaction (HCI), is central to the development of effective, efficient and enjoyable products. Hassenzahl (2008) defines UX as "a momentary, primarily evaluative feeling (good-bad) while interacting with a product or service." Machine learning (ML), within the field of artificial intelligence (AI), is the future of technology. Jordan and Mitchell (2015) define ML as "the question of how to build computers that improve automatically through experience." The inevitable cross between UX and ML is the future of technological products.

Both UX and ML are interdisciplinary fields, which makes integration complex. Therefore, thoroughly investigating the fields independently is critical in understanding and exposing the possibilities of integration. Our goal is to gain substantial knowledge of UX and ML in order to have a sound foundation before examining their relationship. We present a literature review that provides a comprehensive overview of past developments, current progressions, and future implications of the fields both individually and collectively. Our hope is that our research will provide value by adding to the stirring conversation about UX and ML.

Our primary research question is "what is the relationship between user experience and machine learning?" We broke down this question into straightforward sub-questions such as "what is user experience?" and "what is machine learning?" We investigate these questions by dividing our literature review into three areas: (1) UX, (2) ML, and (3) UX and ML. We first present our methodology for finding academic and non-academic papers, with an emphasis on eliminating potential bias. We then provide background overviews of the UX field and the ML field individually. UX topics covered include design, evaluation, and future directions. ML topics covered include current progressions and future directions. This background provides a foundation for the next part of our review, the cross between UX and ML. We consider the relationship, the advantages, the challenges, and the future implications.

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2 Methodology

Our literature review investigates UX and ML as separate entities and how they work together. By using scholarly articles such as literature reviews and studies, we examine the challenges and trends of ML and the various ways designers use it. We review what is working, what is not working, and what work needs to be done to improve UX. While scholarly articles will provide a consensus of how ML is being used in UX, using non-academic pieces, such as op-eds, articles, or even blogs from professionals in the field, will provide us with greater detail of what is going on in both industries. The usage of non-academic papers will help us learn more about the technology needed to perfect the concept of ML, the challenges of working with ML, as well as problems that have not risen in the academic world. Using scholarly and non-academic papers will help us eliminate any potential bias in our ongoing work and evaluation. We consider all viewpoints of UX and ML, whether positive or negative.

3 Background

In this section, we introduce the concepts of UX and ML separately to establish a conceptual foundation for our main research direction. Moreover, we take a close look at each of them with regard to how they function in their respective areas. For UX, we emphasize its design and evaluation processes, since they are the most promising parts of UX in applying new technologies. For ML, we pay more attention to its current and potential uses across various applications, with a purpose of making the most out of ML techniques to enhance UX.

3.1 User Experience

UX is an emerging and fast-growing research area that has been explored during the recent two decades (Gross & Bongartz, 2012). Although the concept of UX and an increasing number of UX-related methodologies, tools and techniques are being accepted and employed by practitioners in the industry, a universal and clear definition of UX is yet to be developed. Generally, UX determines users' satisfaction when they are interacting with a product or service. The International Organization for Standardization (ISO) 9241-940 defines user experience as "person's perceptions and responses that result from the use and/or anticipated use of a system, product or service" (ISO, 2017). This definition is viewed as somewhat vague by lacking further explanation of terms such as "anticipated use," but still aligned with the proposition by many researchers that "UX is dynamic, context-dependent, and subjective" (Law, Roto, Hassenzahl, Vermeeren, & Kort, 2009). Besides these attributes, Hassenzahl (2008) also emphasizes the "present-orientedness" of UX, by asserting "the primary object of judgement remains the stream of passing momentary feelings".

A term often associated with UX is usability; it is widely recognized that UX extends usability and there is a tight connection between the two. While usability focuses on product performance, such as efficiency, effectiveness and satisfaction (Bevan, 2009), UX models focus on well-being resulting from interaction between human and system, product or service (Hassenzahl, 2008). Usability facilitates the implementation of a good UX by making the whole process more achievable and streamlined. So there is chance for new technologies to enhance UX indirectly through improving performance of usability attributes. From analyzing the definitions of both terms, we assume usability as more objective when measuring system performance. Whereas UX, by definition, represents all the user's perceptions and responses, whether subjective or objective. In this sense, we tend to include usability in the scope of UX to understand the latter more comprehensively.

3.1.1 UX Design

When speaking of UX design, some people simply perceive it as the combination of functionality and aesthetics, which is far from the truth. To understand how the UX should be designed, one must figure out what leads to a good UX in the first place. Hassenzahl (2008) asserts that "fulfilling the human needs" results in good UX. This explication could enlighten designers about how to implement a good UX. Different human needs generate different requirements and perceptions of experience. In order to increase users' satisfaction with accomplishing their goals on both practical and emotional levels, designers should clarify those needs and bear them in mind to design products or services with features corresponding to each need. For example, if not taking various user needs into consideration, designers might not be able to create "shuffle mode" in multimedia players. Because this mode provides users with randomness, which might be a stimulation leading to new thoughts and discoveries. Sometimes the uncertainty of it also brings surprises to users. These are all non-instrumental user needs that are typically ignored in an engineering approach (Leong, Howard, & Vetere, 2008).

Hassenzahl (2008) notes the difference between "pragmatic qualities," or functional characteristics, and "hedonic qualities," or emotional characteristics. He recognizes that both types of qualities must be fulfilled in creating a good user experience. Hassenzahl (2008) also points out designers' need for inspiration. This requires them to deeply delve into the details and uniqueness of users, products and the context surrounding them. Nevertheless, he also suggests that designers employ "the already cumulated knowledge available through, admittedly, reduced, but proven models" as off-the-shelf criteria to assist themselves in both design and evaluation stages.

It is widely known in the industry that UX design is an iterative process. Evaluation is an indispensable part throughout the progression of UX design projects. This calls for the adoption of various measurement methods in UX design practices. Researchers have been studying on this topic for many years and some of them have successfully developed UX evaluation frameworks or strategies with high practical values.

3.1.2 UX Evaluation

The UX design process is typically a variation of four phases: research, analysis, design and evaluation. As discussed, UX design is an iterative process, with design and evaluation being the most cyclical; repetitious design and evaluation is important for achieving maximum usability. As MacDonald and Atwood (2013) articulate, "design and evaluation are closely related activities that support and inform each other." Similarly, Zarour and Alharbi (2017) argue "user experience is tightly coupled with usability." Now that we have defined UX and discussed UX design, we will examine UX evaluation.

As mentioned in the previous section, UX is a subjective field. Zarour and Alharbi (2017) study the relationship between UX design and evaluation, express the need for a "scientific consensus," and propose a universal "UX framework." The authors first conduct a literature review to gain insight on UX design and evaluation best practices. They determine three elements that comprise UX design and evaluation, "dimensions," "aspects" and "measurements," and build a framework around them. The dimensions consist of five categories of primary study in UX, including "value," "user needs experience (NX)," "brand experience (BX)," "technology experience (TX)" and "context." The aspects consist of attributes that impact UX, and are nested under each dimension. For example, the authors describe pragmatic qualities and hedonic qualities as aspects, and group them under the NX dimension. Finally, the measurements consist of methods that test the realization of each aspect. For example, the authors suggest measurements like questionnaires and interviews can validate the NX dimension is met.

Similar to Zarour and Alharbi (2017), MacDonald and Atwood (2013) recognize the need for a universal UX framework, specifically urging for the creation of a "more holistic vision for UX evaluation." The authors analyze the "past, present, and future" of evaluation in human-computer interaction and propose strategies for developing present and future evaluation systems. Use contexts and technologies are continually evolving, prompting the need for adaptive design methods and subsequently adaptive evaluation methods. Like Zarour and Alharbi (2017), MacDonald and Atwood (2013) differentiate between pragmatic qualities and hedonic qualities, further arguing for a measurement method that seamlessly integrates both types of feedback.

3.1.3 Future Directions of UX

It is clear that UX is a dynamic discipline that is continually evolving. St. Amant (2017) stresses a plain and simple fact: "everything changes over time." The author calls for a re-examination of the UX field as a whole, outlines questions for reflection, and proposes a future focus. He argues that this new focus should be on context of use, a concept we have seen appear many times. As St. Amant (2017) describes:

> After all, it is the dynamics of overlapping and interlocking social, political, technological, and other contexts that affect how we use items to interact with the world around us.

St. Amant (2017) proposes six common questions to ask in studying context of use: "who, what, when, where, why, and how." He describes how modern technology makes each of these questions increasingly complex. For example, he asserts that shifting contexts require designs to be more personalized and target "a wider range of smaller and more focused groups," complicating the "who" element. Similarly, shifting contexts require revising designs to meet different objectives, further complicating the "what" element.

Hassenzahl (2008), Zarour and Alharbi (2017), MacDonald and Atwood (2013), and St. Amant (2017) all assert in different capacities that the UX framework needs to be revisited and rethought. Hassenzahl (2008) notes that successful design requires a thorough understanding of not only the user, but also the use context. Zarour and Alharbi (2017) make it clear that context is complex because it "relates to all dimensions together and surround them." MacDonald and Atwood (2013) argue that ubiquitous computing, among other factors, is changing the contexts in which interactive devices are used. St. Amant (2017) outright calls for the future focus of UX to be on context. We hypothesize that the questions St. Amant (2017) proposes about the relationship between context and user experience can be answered with machine learning, which we begin investigating in the next section.

3.2 Machine Learning

Now that we have provided an overview of the UX field, we next survey the ML field. Jordan and Mitchell (2015) present an overview of ML by discussing its origins and current trends. Louridas and Ebert (2016) also provide an overview of ML, but with a focus on implementation techniques and technologies. Both Jordan and Mitchell (2015) and Louridas and Ebert (2016) agree that the recent explosion in machine learning is fueled by access to greater computational power and larger data sets.

Jordan and Mitchell (2015) define ML as "the question of how to build computers that improve automatically through experience." ML, within the field of artificial intelligence, has experienced exponential expansion in recent years. "It is one of today's most rapidly growing technical fields, lying at the intersection of computer science and statistics, and at the core of artificial intelligence and data science" (Jordan & Mitchell, 2015). Louridas and Ebert (2016) agree that ML is "the major success factor in the ongoing digital transformation across industries."

According to Jordan and Mitchell (2015), Many ML developers are finding that training a system through experience can be easier than programming a system manually. The system can learn the correct input-output behavior over time rather than relying on the manual entry of every potential input and output. Louridas and Ebert (2016) describe this idea in simple terms: the computer learns from examples and then performs the task with new data. This idea of improving task performance through a training experience is made possible through "learning problems" (Jordan & Mitchell, 2015). Jordan and Mitchell (2015) expand on this idea by giving the example of using ML to label credit card fraud; the system can be given a history of transactions labeled as fraudulent or not fraudulent, and the machine can use the training experience to detect future fraudulent transactions. There are a wide range of machine learning problems, and a wide variety of ML algorithms to cover them.

Louridas and Ebert (2016) go one step further by discussing machine learning strategies and tools that can be used for each approach. ML is divided into two types of learning strategies, "supervised learning" and "unsupervised learning," with two types of algorithms associated with each strategy. Supervised learning training sets provide the input and the correct output. Alternatively, unsupervised learning training sets provide only the input. Various tools are used according to the type of algorithm, and two coding languages, R and Python, are used depending on user preference. Louridas and Ebert (2016) emphasize that "no single tool will do;" good software engineers know how to use multiple tools and are able to apply them thoughtfully to different situations. Now that we have an idea of what machine learning is, we will examine its current progressions and its future directions.

3.2.1 Current Progressions of ML

One popular trend within ML over the past several years has been an increasing emphasis on using deep learning to analyze large data sets. Deep learning is "a subcategory of machine learning algorithms that use multi-layered neural networks to learn complex relationships between inputs and outputs" (Dong, 2017), where neural networks mimic networks of biological neurons in the brain. This new approach has several advantages. For instance, deep learning can model vary general non-linear relationships without knowing the form of the relationship in advance. This allows one to avoid what is termed in ML feature engineering, as described in Baldi, Sadowski and Whiteson (2014):

> A common approach [in ML] is to combine shallow classifiers with high-level features that are derived manually from the raw features. These are generally non-linear functions of the input features that capture physical insights about the data. While helpful, this approach is labor-intensive and not necessarily optimal; a robust machine learning method would obviate the need for this additional step and capture all of the available classification power directly from the raw data.

For all its advantages, however, deep learning retains a number of downsides. These include requiring much larger training sets than traditional ML models and requiring more computing resources (Dong, 2017). According to Dong (2017), deep learning also requires a lot of "manual fiddling" by the user to make it function properly, requiring "a combination of intuition and trial and error."

As pointed out by Dong (2017), traditional ML methods are still very powerful, and in fact most ML applications still make use of traditional models. Dong (2017) argues, however, that more work needs to be put into building ML-oriented infrastructure for the storage, management, and retrieval of data in a manner that is ML aware, and promotes ease of use of this data as the basis for ML models. He adds that the future of ML depends on such systems to seamlessly integrate the entire ML architecture. This could have direct implications for what the merger between UX and ML could look like once ML infrastructure improves to smoothly work with data.

3.2.2 Future Directions of ML

The major contributions to the progress in ML are made by two drivers. One is new theoretical and practical discoveries, the other is the increasing availability of large data sets and powerful computing capability with lower cost. The latter enables ML systems to create and maintain more sophisticated data structures at a larger scale (Jordan & Mitchell, 2015).

Despite the achievements of ML so far, there is still a huge chasm between ML and human learning. Greenwald and Oertel (2017) summarize five expected capabilities associated with human learning that ML could possibly develop in the future. The first is "feature selection," which requires ML algorithms to select appropriate sets of features at appropriate precision from the input data. While humans are good at feature extraction, selection and generalization, ML systems are relatively fragile when facing changes in the feature set. The second is "robust representation schemes and interpretability." The representation scheme refers to how and what learned information is preserved in a ML system. This scheme impacts the way other operations utilize the learned information, making it either easier or harder. Therefore, flexibility is desirable as a property of the representation scheme. Another use of ML systems' internal representations is to help form explanations of how outcomes are derived from input data. People are requesting this kind of clarification due to trust issues. The third is "transfer learning and 'one-shot learning'." This brings forward the notion that humans perform perfectly well in finishing new tasks on the basis of only a limited amount of previous knowledge and experience, benefiting from the human ability of feature extraction and association. In contrast, ML algorithms require not only plenty of training data, but a high relevance between data and the specific task, to reach an acceptable level of accuracy when making predictions or classifications. The fourth is "continuous learning," which is a natural process occurring in every human life. On the other hand, on account of the task-oriented nature, ML systems typically stop learning at some point. Excluding situations where the halt is a must, it is clear that a continuous course of learning will lead to a continuous growth in ML system performance. The last desired capability is "learning and adaptation in time-varying contexts and environments." This perspective re-emphasizes the human ability of generalization and adaptation, lacking of which results in a series of periodical retraining by ML algorithms (Greenwald & Oertel, 2017).

4 User Experience and Machine Learning

We have provided ample insight into the fields of user experience and machine learning individually. It is clear that UX and ML are two convoluted technological fields that have seen rapid expansion in recent years and only continue to grow. Combined, UX and ML have the potential to transform how humans interact with technology. According to Lovejoy (2018), ML "will cause us to rethink, restructure, and reconsider what's possible in virtually every experience we build." In the next part of our literature review, we research and discuss the integration of UX and ML, including the relationship, the advantages, the challenges, and the future implications.

4.1 Relationship Between UX and ML

User experience and machine learning are complex, which further complicates their relationship. Lovejoy (2018) thoughtfully describes the relationship as "human-centered machine learning." The author investigates how ML can enhance UX through the lens of a case study at Google, and reveals his major takeaways along the way. Lovejoy (2018) emphasizes the importance of ML staying "grounded in human needs," and asserts that designers must understand the basics of ML in order to apply it successfully. His major conclusion is that ML needs to be designed with purpose, because computers cannot determine human problems to solve. He also notes that machine learning is ineffective if implemented poorly; "if a human can't perform the task, then neither can the AI." Ultimately, Lovejoy (2018) sums up his findings about integrating UX and ML into a single sentence:

> …it starts by remembering our roots: finding and addressing real human needs, upholding human values, and designing for augmentation, not automation.

Jordan and Mitchell (2015) contribute to the discussion on the relationship between UX and ML by examining how ML algorithms can learn from large data sets to create personalized experiences for individuals and groups of individuals, thanks to ubiquitous computing. These personalized experiences created by ML are largely based on context of use, which we know is an important component of UX.

Further, Shankar, Louis, Dascalu and Hayes (2007) present an empirical research study they conduct that focuses on the relationship between UX and ML, specifically how ML can utilize context of use. The authors investigate how a user interface (UI) can examine environmental information to improve usability and subsequently UX. The experiment applies the framework to a specific scenario, a context-aware calendar application, with the ultimate goal of generalizing the framework for broader incorporation. Similar to Hassenzahl (2008), Zarour and Alharbi (2017), and St. Amant (2017), Shankar et al. (2007) emphasize that individual user preference of an application depends on the context of use. The authors consider two UI usability metrics that contribute to UX: effectiveness and utility. A UI is effective if it does "what it is supposed to do," and a UI provides utility if it has "the right kind of functionality." They ultimately determine that these metrics can be enhanced through ML by creating adaptive user interfaces based on individual user preferences.

4.2 Advantages of UX and ML

The main advantage of integrating UX and ML in designs is the possibility of creating new services within web, mobile, and internet devices (e.g. driverless car) applications. ML algorithms may be used by designers to predict a user's responsiveness to various pieces of information, such as advertisements or recommendations, in order to tailor content according to the individual's unique preferences and what they are "more likely to click on" (Lepp, 2014). These preferences or behavioral tendencies would be inferred by the model based on user data, and continually updated as user preference and behavior evolves. This will free designers from designing for the majority, and allow them to expand their target base to include groups that would not otherwise be feasible.

4.3 Challenges of UX and ML

Due to its capabilities, machine learning can be seen as a way to positively enhance user experience, but there are challenges of using the technology. Dove, Halskov, Forlizzi, and Zimmerman (2017) conducted a study to determine how UX designers are regarding usage of machine learning as a design material and asses the difficulty of using it. In Dove et al. (2017), forty-three people responded to the survey that raised three major challenges:

> ...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.

The first challenge, which discusses what ML can be, brings up the issue of whether the designers understand its capabilities and limitations. ML requires large amounts of data to train the model that designers and developers created. For example, one thing that determines whether machine learning works is the data's relevance to what designers want to predict, which means that it is more than just inputting data. The study created by Yang, Scuito, Zimmerman, Forlizzi and Steinfeld (2018) further enhances this idea by showing that most of the participants "rarely spoke of ML in technical terms" and often "described the capabilities of ML as it related to the user's utility." Designers cannot fully take advantage of ML's powerful capabilities if there's a lack of knowledge on the technical side of ML, which includes statistics, data analyzing and programming.

The second challenge, working with machine learning as a design material, is similar to the first challenge in that not being able to comprehend the full potential of machine learning can cause setbacks of using it as a design material due to lack of understanding. According to Yang et al. (2018), designers "overlook simple opportunities to utilize ML" and that "design-led innovation of ML is rare." That is why most companies continue to use traditional ML methods instead of creating new ones that might work better with the data. Yang et al. (2018) surveyed thirteen experienced UX designers that said "designing the user interaction was the 'actual challenge.'" The lack of knowledge on how to use ML in designs leads to a lack of innovation, and can lead to failure of desired results. For example, if designers are using the same type of model for each dataset, they will not receive the desired results or it will take more time to make the model work. Individualized ML models need to be created for each dataset to improve the overall user experience since that model will continue to learn from the consumers.

An intriguing topic that was raised regarding working with ML was that participants working at an AI-focused company had a more "significant advantage" compared to designers that worked at smaller or less AI-focused places (Yang et al., 2018). Large companies usually have teams of data scientists "giving demos as one way to sensitize their design teams to emerging ML capabilities" compared to smaller companies that had a "limited access" to data scientists (Yang et al., 2018). Without large access to data scientists, designers might not be able to analyze or comprehend the datasets that they are using and how it works with the algorithm.

The last challenge, "concern in designing with ML as a 'black box,' raising ethical questions about the purposeful use of ML," brings up the notion on how to keep the consumer in the mind (Dove et al., 2017). A question arises on the role ethics plays if a system creates an error that affected the consumer, which leads to who takes the blame. A comment made in the study, "can it be trusted to make decisions or take actions on its own?" (Dove et al., 2017) shows that designers should be concerned about what the model. Designers should be asking themselves questions about what is in the model, what type of data is in the model, what the algorithm should be doing and what it is actually doing. By asking these types of questions, designers can help to avoid ethical issues, a biased model and avoiding a model that might scare the consumer.

4.3.1 Education Challenges of UX and ML

Education in UX, interaction design and human-computer interaction does not prepare graduates on how to incorporate ML into their work, according to Dove et al. (2017). In the study, only three people had taken a class that taught them how to "integrate ML into the UX design of products and services" (Dove et al., 2017). Considering that only three respondents, from forty-three, had some training and education in integrating ML with UX in their course, it explains why there are challenges regarding concepts as explained in the first two paragraphs of Section 4.3. UX education must "provide new means" (Yang, 2017) to help designers understand ML and enhancing their technical literacy to be able to collaborate with ML experts.

A way to solve the education gap is by training designers to "work and think with data" and providing "opportunities" for designers to collaborate with data scientists, according to Yang et al. (2018). By being able to interpret and manipulate data as part of their hands on experience, designers can comprehend the statistics and data involved with ML and create new innovative algorithms to integrate into their design.

4.4 Future of UX and ML

Due to these challenges, in order for ML to be better incorporated into UX practice to help reinforce it, there are several questions that researchers and practitioners in both fields should take into consideration and try their best to resolve through innovative and intelligent efforts.

From UX designers' perspectives, more adapted educational resources and programs with respect to ML should be introduced to those who are seeking to utilize new technologies in their design. That said, comprehending the functionality of ML systems is not equal to knowing where and how to integrate ML into UX designs, because "many of these systems have weak connections to divergent user experiences after repeated use" (Yang, 2018). In fact, this problem often manifests as difficulties in finding joint points of UX and ML both in specific designs and the industry as a whole. To uncover more opportunities, there are two things that need to be paid close attention to. The first is existing ML design examples that prove to be working successfully. This is a direct way for designers to get inspired. Yang, Banovic and Zimmerman (2018) conducted a literature analysis and identified three topics that are not being fully explored: deep learning, social network mining and sentiment analysis, which may indicate new research directions and market potentials. The second is user needs. Designers must recognize particular user demands that are seemingly unusual but technically satisfiable through ML. It is likely that some of them could be generalized to a larger group of people and provide value for them. According to Yang (2018), more "sensitizing concepts" need to be produced to help UX practitioners envision new possibilities of applying ML technology to their designs.

From the perspective of ML development, to offer more convenient and comfortable UX, the extent to which ML should reach when aiding people in decision making and other activities is definitely a key issue to be settled in the future. Surely it would be better for ML systems to be more intelligent, but this also raises the concern that ML could become out of control someday. If this situation occurs in the future, UX would be undoubtedly badly damaged. Perhaps researchers and engineers should approach the problem of where to set boundaries for ML applications on a case-by-case basis, which means users and the usage context must be referred to.

One possible solution for ML experts to overcome the barrier between UX and ML is to take UX design principles into account when building ML models or algorithms. For instance, a good UX design does well in both error prevention and facilitating users to recognize and recover from errors (Nielsen, 1994). Likewise, ML technology is supposed to keep improving its output accuracy and have recovery methods prepared for foreseeable errors or breakdowns. Moreover, drawing upon the UX design principle of user control and freedom (Nielsen, 1994), no matter what type of system is being constructed using ML techniques, users should always be guaranteed with the feeling of holding control over the system or the machine, rather than the opposite. This also helps to answer the aforementioned question that "can it (the machine) be trusted to make decisions or take actions on its own?" (Dove et al., 2017). As inventors of these ML applications, researchers and practitioners should avoid blindly trusting and applying algorithms and leave the last word to humans when making high-impact decisions.

As far as cooperation between UX and ML experts, there are some issues that need to be addressed thoughtfully. As Yang (2018) points out, when adding ML to UX design, the problem lies in two aspects: the timeliness and the availability of costly ML materials in such an iterative process. It calls for development of new ML-capable tools that assist with sketching, prototyping and evaluation, as well as new design methodologies that circumvent the use of too many ML developing resources. Furthermore, researchers are supposed to leverage "procedural knowledge of designing ML" to optimize the classic UX design workflow (Yang, 2018). In all of these endeavors, UX and ML researchers and practitioners are demanded to work collaboratively to establish a symbiotic relationship between the two areas.

5 Conclusion

We have examined the relationship between machine learning and user experience by reviewing and analyzing the literature from each field individually and their intersection. It is clear that UX and ML are complex disciplines themselves, complicating integration. In doing so, we have defined the advantages, challenges and future implications regarding usage of ML in UX design.

Among the advantages, we have seen that ML would allow UX designers to individualize content, thereby allowing them to target smaller, more narrowly defined groups than would have been possible without ML. We have also seen that the challenges include overcoming obstacles such as the limited exposure of designers to ML in the educational process and in careers and lack of understanding on how to integrate innovative ML algorithms into a design.

We have determined that going forward, certain steps will be necessary to fully integrate ML into UX. First, UX training and education should include increased exposure to ML topics and their application to UX. Second, better ML ecosystems should be designed. This ecosystem should feature better integration of the entire ML/UX pipeline from data management to model building to design, as per the recommendations of Dong (2017). It should also be built, as stated above, according to UX design principles in order to aid ease of use. We foresee that the design of such a system can positively impact UX design to the benefit of users and designers.

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