Usability Approaches Considering Artificial Intelligence -Machine Learning Techniques and Technologies

ABSTRACT

As algorithms and implementation methods improve, it is pivotal that user interface (UI) engineers develop innovative processes to integrate them into aspects of pre-existing and future applications in a way that enhances the user experience (UX). The objective of this paper is to discuss, in fine detail, the techniques that assist in outlining a prominent execution of a machine learning based UI. In order to understand the mesh between a positive UX and machine learning, it is imperative to analyze the services that have proven their endeavor successful. This research will provide reference that will prove crucial in assisting the future development of the machine learning integrated applications. In conclusion, an effective use of machine learning integration is possible and achievable by analyzing similar applications that have already paved the way.

INTRODUCTION

It's no secret that machine learning is becoming more relevant and identifiable in everyday life. We encounter it through our phones, our computers, and almost every major application that we interface with. As our desire for simplicity and convenience grows, it is important that the technology innovated to meet these needs meets our unconscious ambition of intermeshing fluidity. We want practical applications with complex inner workings blanketed by a clean and elegant user interface that drives seamless interactions. Good design is everything. We analyze and interpret a wide variety of inputs ranging from layout to ease of interaction. Images, colors, words, and even fonts to represent a variety of different things. They make us feel, they help us understand, but most importantly they help connect us through the beauty of the user experience. We must strive for applications that are useful, usable, findable, credible, desirable, accessible, and valuable. In order to understand the concepts of a good UX, and how they're properties form a cohesive relationship with machine learning, it is enlightening to assess a few major companies and how they dominate their industries. We have chosen to discuss machine learning applications that have heightened the user experience for the luxury electric car manufacturer, Tesla, the streaming giant, Netflix, and for everyone's favorite video sharing service, YouTube.

APPLICATIONS

Tesla's Autopilot System

Areas are becoming more developed than ever leading to new jobs and new innovations. We can only build up or infrastructure so much. It's easy to compound space in the form of buildings, but much more complicated to stack highways and interstates. This growth has led to an increase in traffic that is unprecedented. A typical thirty-minute commute can take triple the time than it should if not more. Companies like Tesla are aware how frustrating and inconvenient situations like this can be. Using machine learning concepts such as machine vision, Tesla is pushing the conventional norm to exponentially increase the UX of the "daily drive". Although this endeavor is not fully perfected, engineers are closer than ever which could possibly lead to the normalization of fully autonomous vehicles.

Using radar, cameras, and ultrasonic sensors, Tesla has created a transportation medium that is aware of its surroundings. These technological advancements have led to a realistically affordable luxury vehicle that is capable of autonomously steering, merging, parking, and much more (Ingle, Phute, 2016). The radar is useful in detecting moving objects from a distance but isn't very useful for objects that are motionless. Using the various cameras around the vehicle, a Digital Neural Network (DNN), and core object detection principles, the vehicle is able to map out and detect the pertinent variables that could possibly come into play such as other vehicles, road curvatures, and pedestrians. The ultrasonic sensors allow for detection of what can best be described as blind spots (Ingle, Phute, 2016).

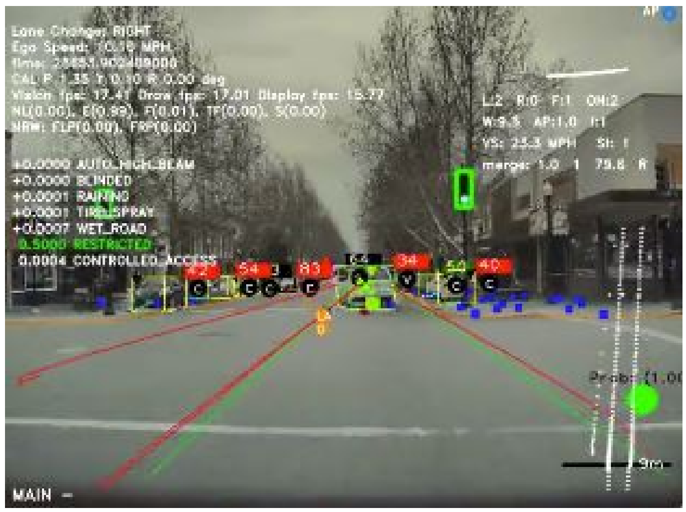

Figure 1: Tesla's Neural Networks displaying live object semantic segmentation, object detection and monocular depth estimation for its Autopilot AI (Tesla, 2020)

The beauty behind Tesla's Autopilot AI is how well it is integrated and the simplicity of activating it. Using the autopilot is as easy as selecting a destination and toggling the autopilot button. Tesla also provides the ability to change core autopilot settings to best accommodate the driver. These settings allow you to determine if you want to opt into the autosteer beta, set a custom following distance, or even set various lane change options such as your lane change speed.

Tesla provides the perfect model for demonstrating what a clean integration of machine learning should look like. Tesla's Autopilot AI is easy for the driver to activate, easy for the driver to customize, and in all honesty, the interface looks beautiful. All these factors compounded together provide a stunning UX for consumers of all backgrounds.

Netflix's Recommendation Algorithm

While there are many applications evident of implementing machine learning to improve the UX, one of the most widely used examples is the recommendation system by the streaming giant, Netflix. Over the past two decades, Netflix has revolutionized the entertainment industry by providing easy and affordable access to premium, personalized content. Through machine learning techniques such as data mining and matrix factorization, they have ushered new standards amongst streaming and entertainment platforms.

Netflix optimizes for accuracy, diversity and awareness. One of their primary goals is to show the user that they are learning; That they're able to adapt to each user of a household in a meaningful way (Amatriain, 2013). Simply put, they want to show they care. This is a key element in their crusade to providing a quality UX that is incomparable. When examining their ranking algorithm, they logically formulate their baseline at popularity. Once the baseline has been established it factors in "features" and "weights" based on predicted user ratings. This is done by using a scoring function that implements "a linear combination of popularity and predicted rating" (Amatrian, 2013). In order for this to work on a large scale, their function must be trained, much like any other machine learning model, by feeding it a dataset of videos and training it to match the expected output by adjusting the weights. Overtime Netflix has experimented with optimization as well as increasing the number of distinguishable features which in turn has decreased error rates (Amatrian, 2013). These improvements have led to the high performing model we interact with today.

One key factor in making all of this possible is that big data that Netflix is able to utilize. They have million user ratings, millions of terms searched, and millions items added to user lists each day. That is all without factoring in the various metadata for each item in their extensive catalog(Amatrian, 2013). This adds to their accumulation of impression data, social data, external data, and various other data features based on "demographics, location, language, and temporal data" (Amatrian, 2013). When dealing with big data, it is imperative to lay the framework for a big data solution. This is what is commonly referred to as the "software architecture". Below is an example of Netflix's personalization system architecture:

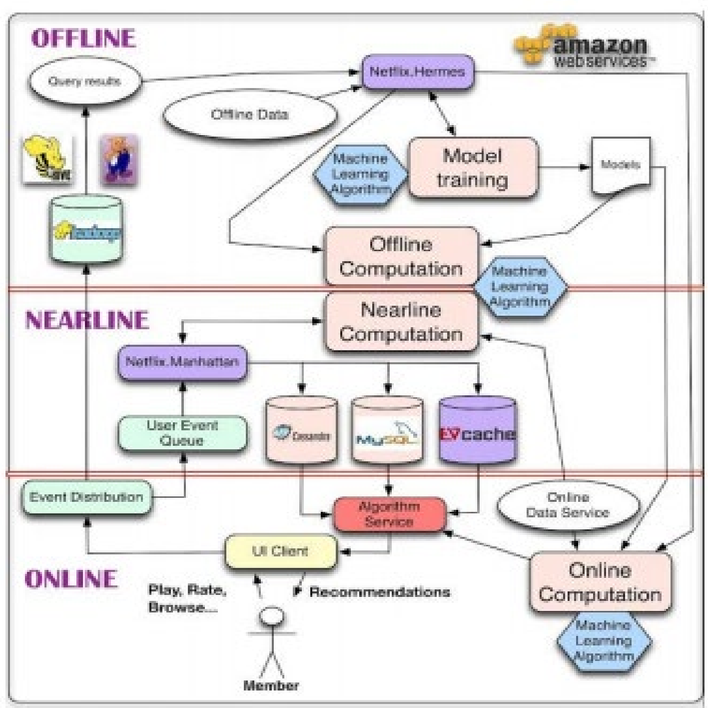

Figure 2: Netflix Architecture for Personalization (Amatrian, 2013)

The YouTube Algorithm

YouTube has been a well-known platform for uploading, watching, and sharing videos. It started out in 2005 and has since grown into the biggest videos hosting and sharing site globally. As it grew, YouTube has gone through a few iterations to create its algorithm to increase the user experience of the people on the platform. This algorithm is currently known within the community as the "YouTube Algorithm" and its purpose is to recommend videos to its viewers. This algorithm is a great example of a company using machine learning to give their users a better experience roaming their platform, as well as a good example of updating the parameters of the machine learning algorithm.

The first iteration of the algorithm lasted from 2005 until 2012. This iteration only cared about one thing for a video and that was view count. In other words, how many times a video was clicked on. The logic was simple: if more people clicked on the video, the video must be good and should be recommended to more people. However, this system was flawed. As Paige Cooper has stated, "Obviously, this system tended to show people a lot of clickbait: misleading titles and thumbnails proliferated. Users would click, but then feel tricked, probably a little annoyed, and then abandon videos partway through. Eventually, YouTube realized that their user experience was going down the drain and changed tacks." (Cooper, 2020). This is where the second iteration of the recommendation algorithm was implemented.

The second algorithm was introduced around 2012. This algorithm revolved around watch time. The algorithm rewarded videos that retained more attention to their viewers rather than videos that made a view click one the video and quickly click off of it. As stated on the YouTube Creator Blog, "Now when we suggest videos, we focus on those that increase the amount of time that the viewer will spend watching videos on YouTube, not only on the next view, but also successive views thereafter.

If viewers are watching more YouTube, it signals to us that they're happier with the content they've found. It means that creators are attracting more engaged audiences. It also opens up more opportunities to generate revenue for our partners." (YouTube Creator Blog, 2012).

In 2016, YouTube formally introduced the Algorithm and wrote a whitepaper about it. About said algorithm. It was revealed in this paper that the YouTube Algorithm uses a machine learning technique known as "Deep Neural Network" or "Deep Learning". The paper also showed an over-simplified illustration on how the system works.

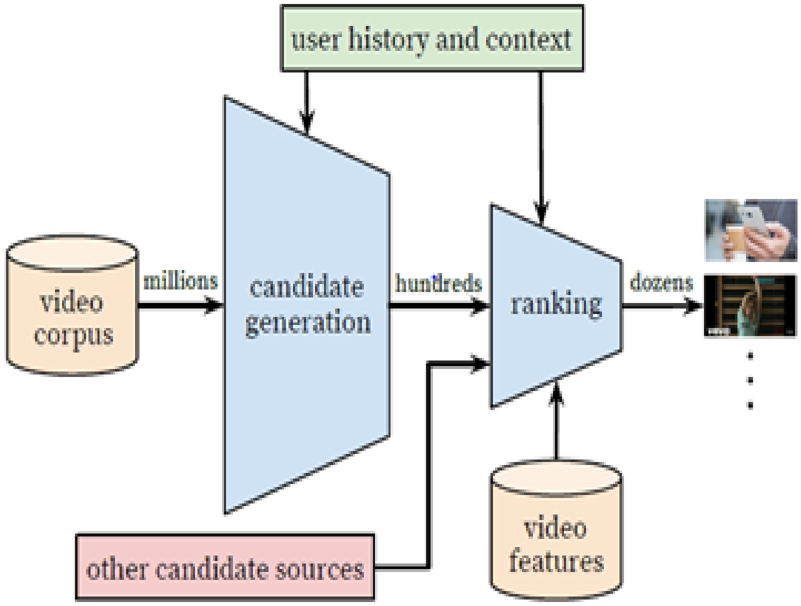

Figure 3: Recommendation system architecture demonstrating the "funnel" where candidate videos are retrieved and ranked before presenting only a few to the user. (Covington, Adams, Sargin, 2016)

As shown in the image above, the algorithm is mainly split into two sections: the candidate generation and the ranking. Using the user's history of watching videos, as well as the previous iterations (views and watch duration) as an added factor, the algorithm filters out videos twice to narrow down what to recommend to its users. "This approach performed much better on watch-time weighted ranking evaluation metrics compared to predicting click-through rate directly." (Covington, Adams, Sargin, 2016).

Currently, this algorithm is still being used as of 2020 with some minor tweaks added over the years to further fit their community guidelines. The evolution of the "YouTube Algorithm" is a product of many years of iterations and added factors to a deep learning algorithm to provide the users a better experience on the website and keep them on the website longer.

LITERATURE REVIEW

Machine Learning Techniques To Make Computers Easier To Use

This research paper shows how machine learning can increase the quality of the user experience when using a computer. The paper starts its introduction with a statement explaining why it is difficult to use a computer sometimes. According to Hiroshi Motoda and Kenichi Yoshida, "Computers are still not easy to use. The main reason is their ignorance about the user. Each user has different goals (tasks, resources, criteria, . . .) and different preferences (habits, abilities, styles, . . .). Computer systems do not understand these things." (Motoda, Yoshida, 1998). The paper also states that computers are limited in what user information is given to them. One such information that tends to not be given is the user's behavioral patterns. There are multiple ways a user can interact with something. As stated, "Since each user may do the same thing in a different way, identifying the information that can characterize the user and be automatically collected is crucial." (Motoda, Yoshida, 1998). In other words, for a computer to optimally assist the user, the computer must be able to learn how the user thinks. The paper then goes into the three learning tasks that the computer must perform, the machine learning technique that was implemented, and the user-interface that was used.

"We discuss three learning tasks, command prediction, script generation and file prefetching in a multi task environment." (Motoda, Yoshida, 1998). Command prediction is, as the name implies, a prediction of the next command. This is done in real time and is done by using the user's operational history. The paper proceeds by explaining how "ClipBoard", the UI that is used in the research, constantly records and updates the history and constantly tries to predict the next command. This task is a supervised learning. "Script generation is a batch task that extracts frequently occurring patterns from a large graph representing a history of order of days, generalizes the arguments and generates shell scripts to execute a sequence of operations by a single command." (Motoda, Yoshida, 1998). This means that the computer will try to group a string of commands together under one script based on how often it shows they show up in that string order. This task is done unsupervised. File prefetching is like command prediction. However, it deals with prefetching files into the cache; therefore, it needs to predict further ahead than just one step so the file could load faster. Like script generation, this task is also unsupervised.

The machine learning technique used in this research paper is graph-based induction (GBI). GBI uses pairwise chunking to extract data. In this research, it was used to find frequently used patterns. "It uses a single heuristic: anything that appears frequently is worth paying attention to." (Motoda, Yoshida, 1998). Using GBI, the researchers were able to find patterns that frequently occurred. In addition, it was also able to find classification rules when applied.

This research paper used ClipBoard and Prefetch daemon. These were used because together they can implement the three learning tasks. "The first and the second learning tasks are implemented as ClipBoard which is a window like UNIX shell [26], and the third task is implemented as Prefetch daemon that is hidden from the user." (Matado, Yoshida, 1998). This section talking about ClipBoard and Prefetch daemon explains in more detail on how ClipBoard can implement command predictions and script generations, while Prefetch daemon can implement file prefetching. In addition, it gives an evaluation on how each task works with the programs and how well they performed.

The research paper also included some examples of ClipBoard. This section includes multiple pictures and details about the pictures. This section is split into two parts. The first part shows how ClipBoard performed before using GBI learning. The second part shows how well it performs after the learning. The description suggests that ClipBoard was able to assist the user. "In summary, ClipBoard satisfies the following desirable features: It is a system that does not require a hand-coded knowledge base to model a user, learns in real time, is accurate enough, does not force a user to accept its recommendation (so user has a control), is easy to use, and learns to improve its performance over time." (Matado, Yoshida, 1998).

In conclusion, this article is a research paper that sought out to see if using GBI, a machine learning technique can help users operate a computer with more ease. By setting the goal of the UI to be able perform three learning tasks, it was able to help the user maneuver through the Clipboard UI. This is done by learning the behavioral patterns of the user to be able to predict what the user's next command is. This in turn, has increased the user experience with the program and UI. This research has demonstrated how machine learning techniques could be implemented to increase the usability of computers for the user.

The Relationship Between User Experience and Machine Learning

User Experience

User experience is often thought of as simply a product of visually pleasing design and performance, but good user experience is more reflected by identifying and satisfying human needs and goals. The "shuffle" feature in a music app is an example of function that satisfies a human need for randomness and discovery that might otherwise be ignored in a typical engineering approach. Good user experience must fulfill both "pragmatic qualities," or functionality, and "hedonic qualities," which are more emotionally driven (Carmona, Finley, & Li, 2018). Designers will need to look at individual users and products for inspiration, but proven models can help in developing and evaluating user experience (Carmona, Finley, & Li, 2018).

The design process for user experience is broken into four stages: research, analysis, design, and evaluation. Design and evaluation are highly iterative processes and each help inform the other. In studying the relationship between design and evaluation, Zarour and Alharbi proposed a universal user experience framework comprising three elements: Dimensions, aspects, and measurements. The five dimensions of user experience are value, user needs experience, brand experience, technology experience, and context. Each dimension consists of different aspects of user experience, with the previously mentioned pragmatic qualities and hedonic qualities both falling under user needs experience. Lastly, measurements such as questionnaires and interviews evaluate how successfully each aspect has been implemented (Carmona, Finley, & Li, 2018).

User experience is an ever-evolving field and should be wholly re-evaluated with a focus on "context of use." St. Amant put forward six questions to be considered when examining this area of focus: "who, what, when, where, why, and how" (Carmona, Finley, & Li, 2018). These questions are difficult to answer with "a wider range of smaller and more focused groups complicating the 'who' element" and "shifting contexts require revising designs to meet different objectives, further complicating the 'what' element." Machine learning may be better suited for these complexities and be able to answer these questions (Carmona, Finley, & Li, 2018).

Machine Learning

The development of greater computational speeds and access to more data has made machine learning one of the fastest growing fields and is "the major success factor in the ongoing digital transformation across industries" (Carmona, Finley, & Li, 2018). Machine learning involves systems being trained to recognize patterns using training data and determine the correct input and output for new data. For example, given a data set containing credit card transactions labeled fraudulent and nonfraudulent, the system can detect patterns in the data set to correctly identify fraudulent transactions. Machine learning can be either “supervised,” where the training set contains both the input and output, or “unsupervised,” where only the input is provided (Carmona, Finley, & Li, 2018).

In recent years, a heavy focus has been placed on “deep learning,” which uses neural networks similar to neurons in a brain to identify more complex patterns between the inputs and outputs, though at the cost of requiring much larger datasets than traditional machine learning techniques (Carmona, Finley, & Li, 2018). Despite the rapid progress, there still exists a large gap between human learning and machine learning. Five key aspects to be addressed are “feature selection,” the ability to choose valid features from the input data; “robust representation schemes and interpretability,” what is learning and preserved by the system; “transfer learning and ‘one-shot learning’,” the ability of humans to complete new tasks with limited information provided; “continuous learning,” where humans keep learning, machines typically reach a limit; and “learning and adaptation in time-varying contexts and environments,” the lack of which mandates a routine retraining of the machines algorithms (Carmona, Finley, & Li, 2018).

User Experience & Machine Learning

The relationship between user experience and machine learning as “human-centered machine learning.” For designers to successfully implement machine learning, they must understand the fundamentals of machine learning and its limitations. Machine learning can use context of use to create unique experiences for individual users. A user interface must be effective, “it does what it is supposed to do,” and provide utility, “it has the right kind of functionality.” Both metrics can be augmented by machine learning to create personalized user interfaces. The algorithms can guide design by predicting what individual users are more likely to click on and updating frequently to match user preferences (Carmona, Finley, & Li, 2018).

There are three main challenges to using machine learning to enhance user experience. First is the lack of technical knowledge with regard to machine learning. Large amounts of data must be provided to train the algorithm and that data must be relevant to what user behavior the designer is looking to predict. Similar to the first, the second challenge is designers’ lack of understanding the scope of machine learning. Designers often overlook simple ways to utilize machine learning and are rarely innovated upon in a way that is design-led, often using existing machine learning techniques rather than forming new ones to better suit the input data. Lastly, “concern in designing with machine learning as a ‘black box,’ looks at potential ethical concerns. Can the system be trusted to take action on its own? If the system makes a mistake that negatively impacts consumers, who is responsible? Designers should keep in mind “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” (Carmona, Finley, & Li, 2018).

Providing resources and programs to educate designers in using machine learning will be needed for successful implementation. Designers should also be provided with relevant examples of successful uses of machine learning for inspiration. Limits should also be established for individual cases to prevent the system going “out of control” and negatively impacting the user experience (Carmona, Finley, & Li, 2018). New algorithms will also need to be developed with a direct focus on user experience to be fully effective. As user experience is highly iterative, new tools for implementing machine learning may be developed to improve on timeliness and manage the use of costly resources (Carmona, Finley, & Li, 2018).

Machine Learning as a UX Design Material: How Can We Imagine Beyond Automation, Recommenders, and Reminders?

According to Google Scholar, there have been over 116,000 publications of scholarly literature referencing machine learning in the past year alone. Whether you're for or against it, there is no denying that machine learning is the spark that will light the fire of the next technological revolution. Inciting a revolution is no task that should be taken lightly. We need designers and engineers who have the drive to innovate and create the systems of tomorrow, today. In "Machine Learning as a UX Design Material: How Can We Imagine Beyond Automation, Recommenders, and Reminders?", Yang describes her involvement in applications involving autonomous vehicles, clinical machine learning driven decision support systems, and context-aware mobile services. She also delivers a glimpse into feasible machine learning applications and their User Experience (UX), the addition of UX to current machine learning systems, and dynamic challenges that encapsulate the use of machine learning as a design medium (Yang, 2018).

Yang was asked by a team of bioengineers to design a machine learning application that would determine when to implant an end-stage heart failure patient with a mechanical heart pump. While most would regard this as a useful and realistic application of machine learning, the medical workers that Yang would be designing this system for did not (Yang, 2018). Although the system would serve a complex function that would require extensive analysis to the untrained eye, Yang and her team determined the application wasn't feasible after interviewing and overseeing numerous clinicians spanning multiple implant centers. The clinicians interviewed shared the popular opinion that it was a rather easy call to make based on the patient data which would ultimately render the software/machines pointless (Yang, 2018). Yang and her team proved to be resilient and in turn sought to develop something that would realistically benefit the average practitioner. With the help of clinicians, the team was able to identify a common problem that truly benefited from a machine learning based solution (Yang, 2018). As seen in the team's actions, they demonstrate the importance of the user-centered design (UCD) process , a common process used to streamline UX design, by addressing the user's needs.

As machine learning continues to grow, companies are finding more ways to implement it in their current business model and existing products. As these implementations make their way into the homes and hearts of the user, the ease of use is imperative. It is important that designers implement machine learning in current applications and interfaces in a way that adds value to their organization and serves a purpose that aids the user. It is also important to determine the cost of converting existing applications. The UCD process doesn't currently address machine learning and machine learning conflicts with some of the underlying mottos prevalent in the UCD such as "fail fast, fail often" (Yang, 2018). This poses obvious problems when developing an outline or framework to drive the workload. Out of necessity for a more streamlined application integration process, machine learning needs to be inserted into the industry standard of design practices and workflow (Yang, 2018).

Throughout Yang's machine learning based UX resume, she has learned by trial and error, the shortfalls that can slow a project's traction. One of the most important phases of the software development life-cycle (SDLC) is the planning phase. A common hurdle for a machine learning driven user experience (UX) is oversight and the lack of consideration during the SDLC planning process (Yang, 2018). If machine learning and UX isn't addressed in the early stages of the SDLC, it will ultimately lead to a software requirement phase where all functional requirements are void any form of machine learning implementation (Yang, 2018). Additionally, the problem set will prove to be of great cost in terms of time, money, and resources further along in the SDLC. Yang also addresses the knowledge deficiency and lack of resources that plagues the UX design community. Many designers fail to articulate practical applications of machine learning in UX (Yang, 2018). After conducting a consensus amongst UX practitioners, many were found unable to determine fitting applications for machine learning and we're only able to reference outdated implementations such as spam filters (Yang 2018). These underlying issues are where Yang derives the necessity for design research. She believes the research will serve as the bridge and will allow designers to expand their conceptualizations of a machine learning encapsulated UX design. Another common issue is that many design teams do not have the assistance of data scientists which poses a problem for any machine learning models due to the significantly large data sets that need to be analyzed and processed for a successful and efficient application (Yang, 2018).

In summary, while there have been many advances in the field of machine learning, there are still a number of user-centered design process improvements to cultivate the user experience. Thanks to Yang's research and experiences, we are able to identify common problems and begin to develop solutions for an improved design process that supports machine learning. Through research, collaboration and communication, we can increase the quality threshold of a machine learning based user experience.

Investigating How Experienced UX Designers Effectively Work with Machine Learning

In this paper, Yang et al (2018) interviewed thirteen experienced UX designers and found they had little experience with machine learning and did not regard it as an important tool for improving their skills as designers. The increasingly larger role machine learning plays in creating a satisfying user experience from the handling of mundane tasks like filtering spam from the user's email inbox to creating a personally curated news feed would seem to imply UX designers have become more experienced and competent with machine learning as a tool in their design process. However, the research available shows otherwise, with surveys of UX designers revealing the subjects had little understanding of the potential uses of machine learning and failed to notice even simple use cases that machine learning could enhance. It was also noted that UX designers tended to be introduced into the team during the final phases of a project, after functionality had all been determined (Yang et al 2018). Recent approaches to address this problem have focused on creating more opportunities and better toolkits for educating designers in the use of machine learning. Instead, Yang et al (2018) wanted to look at the design process of several experienced UX designers to see if the underlying assumptions used to create educational materials and tools for the use of machine learning as a design material. "The interviews produced several interesting findings: 1) Designers shared that they knew very little about how ML works, and this was not a priority for them. They instead used designerly abstractions and popular examples to explain what ML is and to communicate design ideas with each other. 2) ML projects are longer in preparation and scope than other design projects. During the preparation stage, designers evolved their ideas in close collaboration with data scientists; They did not deliver fully formed designs to a technical team. 3) Designers "play" with quantitative data during all phases of a design project" (Yang et al 2018).

The methodology of Yang et al (2018) emphasized experience in selecting the participants in their interviews, noting that many prior works had used relatively less experienced designers and examined their struggles. They wanted to contrast the design process of UX designers that rely on more traditional methods versus the design process of those designers with many years of experience using machine learning as a design material. The initial subjects were drawn from the authors own network of alumni, mostly former master's students now working in industry, while the rest were recommended by those designers. All interview subjects had at least four years of relevant experience, with six of the thirteen having more than ten years of experience. The interviews were retrospective as looking at current practices was deemed impractical as the design process often takes place over months and also designers were limited in what could be discussed regarding current industry projects for competition reasons. All of them were asked to complete a survey before the interview, which gave their education and prior work experience, and also asked them how well they knew the concepts being discussed (Yang et al 2018). The interviews drew particular attention to two areas of concern raised by prior research: lack of understanding of the capabilities of machine learning and the timing of when designers were brought on board the team for projects. They were also asked to draw an illustration of how their design worked to get a better understanding of how these designers thought about machine learning. The interview concluded by asking them to describe differences in how they work on projects which utilize machine learning versus projects that don't and if there was anything they wish they had known about designing with machine learning before starting their careers (Yang et al 2018).

Yang et al (2018) categorized their findings into three different themes. First, what the subjects did to better their understanding of machine learning as a design material. Nearly every subject acknowledged their limited understanding of machine learning and only one had ever taken a course on the subject, which was entirely online and completed post-graduation. Notably, the subjects did not view the lack of technical knowledge as a hindrance and viewed the challenges of UX design as more about designing user interaction. Several the illustrations showed a line between users and the technology, with a series of connected boxes representing the back-end design. One of these boxes was labeled machine learning and was noted as "not so simple" by the subjects (Yang et al 2018). The way UX designers discussed machine learning differed greatly from how educational material was meant to teach them. They rarely used technical terms and spoke more in abstractions and examples. When asked what machine learning does, one interviewee relied, "Some try to recognize intent, a bit like auto-correct. Some are intent predictions like Clippy" (Yang et al 2018). Everyone had a different number of abstractions and examples to draw from, with those having the most seeming more confident working with machine learning.

The second theme focused on changes in the design process caused by machine learning. None of the participants had been part of the team for the entire duration of the project, so a concrete time could not be estimated. However, the subjects did agree that machine learning lengthened the time span of a project by a great deal. The process began with a long beginning stage where the designer would look at available logs from existing services already provided to them by their company, often searching these logs for patterns they suspected might be there rather than data mining to find potentially surprising patterns (Yang et al 2018). The designers would discuss with data scientists the possible goals for improving user experience, often leading away from working with machine learning and pursuing a passable alternative. The second stage focused on focusing the goal down into one valuable feature that could be realistically implemented. This was often the stage UX designers were brought on board for the project. Stage three had UX designers evaluate how users interacted with their design after release, though subjects noted very few of their projects had ever gotten to this stage (Yang et al 2018).

The last theme dealt with the data culture that had developed. When probed on how students could become more understanding of the capabilities of machine learning, they discussed the data-centric nature of their environments. "They spoke of the importance of learning to speak the language of quantitative data and data science (e.g., telemetry, analytics, A/B testing, covariance, correlation)" (Yang et al 2018). These concepts were also brought upon by the participants in the survey conducted prior to the interview. To adapt to this environment, the subjects would engage in new design activities, using both methods that were both qualitative and quantitative, honing new skills for collecting telemetry data and for creating visual aids to better understand the data they were collecting (Yang et al 2018).

Rather than instructing designers in statistics and algorithms, Yang et al (2018) conclude interpreting and manipulating quantitative data to be the more valuable additions to designers' skillsets. Cooperating with data scientists was also observed to be the most effective practice. Opportunities for further research that were identified include: "1) developing designerly abstractions of ML's technical capabilities, 2) developing exemplars and sensitizing concepts of ML-enhanced designs, and 3) creating boundary objects that bridge UX and ML expertise" (Yang et al 2018). Abstractions helped frame the value of machine learning and move past technical capabilities when designing. Exemplars were also common in addition to abstractions, and it was postulated that a detailed list of exemplars would benefit the perceived value of machine learning to designers. Designers who could not consult data scientists suffered and usually fell back on common design choices; tools could be better designed to simulate the role of data scientists and enable designers to evaluate their design sketches (Yang et al 2018).

Designers viewed machine learning as a "black box" and, when designing, inquired "not whether this would work, but in your gut, whether this would be possible on a scale 1-10" (Yang et al 2018). While designers could discuss machine learning without any specific educational experience, it remains to be determined if greater understanding might foster more creative designs. Future research should focus and expand upon the design process that was observed in this study: the problem to be solved by machine learning as first identified, the technical limitations were tested, and then iterated to create the proper implementation (Yang et al 2018). Notable limitations to this study include the small sample size from a niche group of UX designers and also the lack of input from the data scientists and other groups working together with the UX practitioners during the design process.

CONCLUSION

Studies and applications of machine learning span wide and far. Each day, as the problems of the modern world reach new complexities, the need for new and intuitive solutions grows. It is imperative that the solutions arising are integrated in a way that appeals to the average user while exceeding the standards of good UX design. This paper has covered excellent machine learning/AI applications spanning from autonomous vehicles, to individualized recommendation filtering. Impractical applications have also been touched on. Applications such as these highlight why the principles of UX that state a design must be useful and valuable are crucial and must be addressed early in the software development process. Using these impeccable examples of good and bad UX through machine learning/AI integration, we can continue to develop and advance in a way that benefits society.

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EXTENDED RESOURCES

1. A Blog post that talks about the history of the YouTube Algorithm and how to work with it. https://blog.hootsuite.com/how-the-youtube-algorithm-works/

2. A Creator's Blog from YouTube in 2012 discussing why they changed their requirement for the recommendation algorithm and how it works.

   https://youtube-creators.googleblog.com/2012/08/youtube-now-why-we-focus-on-watch-time.html

3. A video on other added attributes to the YouTube Algorithm. https://www.youtube.com/watch?v=AI7asbV5A-s

4. A video on Netflix's use of Matrix Factorization. https://www.youtube.com/watch?v=ZspR5PZemcs

5. An article about the machine learning technique called graph-based induction. http://www.ar.sanken.osaka-u.ac.jp/~motoda/papers/adv_eng_inf02.pdf

6. A 6 minute video explaining "deep learning". https://www.youtube.com/watch?v=6M5VXKLf4D4

7. An article explaining how to apply machine learning basics. https://uxdesign.cc/an-intro-to-machine-learning-for-designers-5c74ba100257

8. A video explaining "how machines learn". https://www.youtube.com/watch?v=R9OHn5ZF4Uo

9. A video explaining the difference between UI and UX design. https://www.youtube.com/watch?v=TgqeRTwZvIo

10. A video explaining the difference between UI and UX design. https://www.youtube.com/watch?v=f_uwKZIAeM0

11. A video explaining UX design. https://www.youtube.com/watch?v=OR0r_L2ztDI

12. Article on UX design characteristics. https://www.interaction-design.org/literature/article/the-7-factors-that-influence-user-experience

13. Tesla Autopilot AI backend information https://www.tesla.com/autopilotAI

14. Tesla Autopilot AI operating instructions https://www.youtube.com/watch?v=Q4MngNzG0K0