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Malsattar, Nirav; Kihara, Tomo; Giaccardi, Elisa

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Designing and Prototyping from the Perspective of AI in the Wild

Nirav Malsattar

Delft University of Technology
Delft, the Netherlands
niravpalsattar@gmail.com

Tomo Kihara

Delft University of Technology
Delft, the Netherlands
playful.intervention@gmail.com

Elisa Giaccardi

Delft University of Technology
Delft, the Netherlands
e.giaccardi@tudelft.nl

ABSTRACT

This paper describes ObjectResponder — a tool that allows designers to use Artificial Intelligence (AI) to rapidly prototype concepts for context-aware intelligent interaction in the wild. To our knowledge, there are currently no available tools for designing and prototyping with AI within the actual context of use. Our application uses Google Cloud Vision to allow designers assigning chat bot-like responses to objects recognized by the smart-phone camera. This enables designers to use object recognition labels as a means to diverge on possible interpretations of the context and start generating ideas that can then be immediately tested and iterated. Initial results suggest that looking at the world from the perspective of the AI may enable designers to balance human and nonhuman biases, enrich a designer's understanding of the context, and open up unexpected directions for idea generation.

Author Keywords

Machine Learning; Computer Vision; Interaction Design; Prototyping;

CCS Concepts

•**Human-centered computing** → *Human computer interaction (HCI)*;

INTRODUCTION

A paradigm shift is beginning to take place in the meaning and use of a camera. Combined with machine learning (ML) based computer vision, cameras are becoming a context-aware agent that can judge things based on what they see. Novel services like 'Amazon Go' use computer vision to provide a cashier-less shopping experience where the customers can just pick up what they want and leave. The demand for interaction designers to understand technologies within the AI domain such as ML to prototype new services has been building up. However, working with ML is a challenge for designers [3]. The issue is not that designers lack technical background, rather the fact that the number of available tools for quickly sketching and prototyping with ML is still

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Figure 1. Example of a designer using ObjectResponder to prototype a smart trash bin that nudges people to recycle.

limited. Some tools exist such as Wekinator[4] and Teachable Machine[7] that allow designers to use ML for designing and prototyping. However, these tools are still limited because they either require technical skills for using the tool (such as with Wekinator) or have been too simplified to have robust prototyping capability (such as Google Teachable Machine). Moreover, no accessible tools are currently available for designers to prototype with ML 'in the wild', that is, accounting for user experience as embodied and situated in specific contexts[13]. These limitations make it difficult for designers to: (a) quickly sketch ideas, prototype early concepts, and iteratively test ML systems, and (b) integrate AI with embodied ideation and rapid prototyping methods.

In this paper we introduce 'ObjectResponder', a tool that takes the perspective of the machine and use it as a starting point for sketching ideas and rapidly testing early concepts of context-aware intelligent systems in the wild (Figure 1). An initial study was conducted with a team of six professional designers from a design consultancy in the Netherlands, with expertise ranging from UX to product design. Preliminary findings suggest that using the perspective of the machine as a starting point for idea generation in the wild enabled designers to experience the limitations and biases of the AI as well as their own biases, thus providing a more nuanced understanding of the context. Results also indicate that the feedback loop between human and artificial

perspectives enabled by the tool helped designers rapidly iterate on ideas and concepts. We begin the paper with a short review of the current HCI research on ML as a design material. We then describe our tool and report on the results of our testing. We end the paper with a discussion on how designers can collaborate with AI in the early stages of the design process.

RELATED WORKS IN THE FIELD

Interest in using ML and AI as a design material is growing within and beyond the HCI community [8]. Researchers are investigating the integration of UX and ML in both design practice and HCI research[10][15]. A survey of fifty-one UX professionals who work with ML reveals that most professionals are frustrated by the difficulty of prototyping with ML[3]. The challenge of working with innovative and unexplored materials is a theme that recurs often in UX research. Buxton argues that the "experience" is the most difficult part to prototype since there is a lack of tools that allow designers to do it[1].

To address this problem, educators are using tools such as Wekinator to help students understand and design with ML in a more intuitive fashion [4]. However, the software works only on a laptop, thus making it difficult to prototype experiences in the actual context of use. On the contrary, a project like Objectifier [9] proposes an alternative approach towards integrating computer vision and machine learning into the design process within an actual environment. Yet, it also faces the limitation of low accessibility, given that such research-driven experimental hardware is not available for distributed use. To ensure accessibility from a wider audience, we developed an app-based tool that allows designers to use their own.

HOW TO USE OBJECTRESPONDER

The tool 'ObjectResponder' helps designers rapidly prototype and test early concepts of context-aware intelligent systems in the wild. The tool can be used in the following three steps:

Step 1: See from an Artificial Perspective

First, the designers use the camera to look at their surroundings and see how these are interpreted from the perspective of the machine. The tool runs real-time object recognition by using Google Cloud Vision's object recognition framework. For each object that appears in front of the camera, three possible labels are shown. These labels will be used as a starting point for idea generation (i.e. coffee cup) (*Figure 2*).

Step 2: Create a Response

For each detected object label, the designer can set a chatbot-like utterance in the form of a sentence (*Figure 3*). This sentence will be spoken out by text-to-speech function upon detection of the object. These sentence-based responses are used to fake the function of the bot in a manner of Wizard of Oz prototyping [12]. This creates space for designers to ideate on the interaction outcomes without technical constraints.



Figure 2. Seeing from a machine perspective.

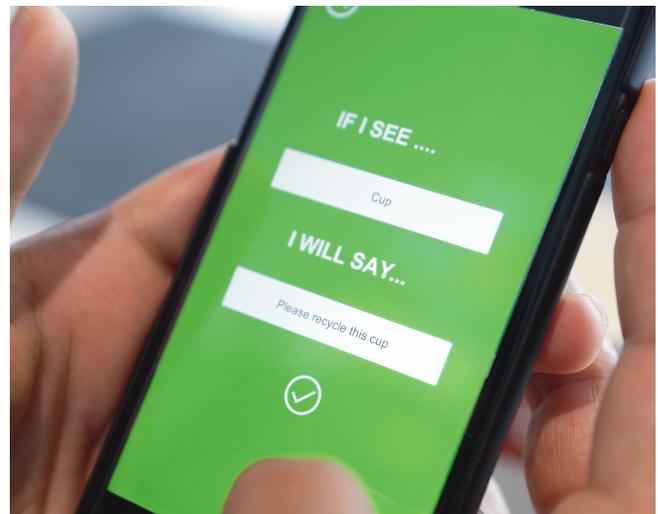


Figure 3. Setting 'if-this-then-that' response to objects

Step 3: Test it Out in the Wild

After setting the sentence as a response to the detection of the object, the designer can then place the smartphone in the environment and test out the prototyped interaction. We provided designers with a smartphone holder which they could use to attach the smartphone to any existing objects. In the case of *Figure 4*, the designer has attached the smartphone to a recycling bin and set the phone to say "Please recycle this cup", when a cup is detected near the wrong bin (*Figure 4*).

IMPLEMENTATION

The app can be used with any smart-phone with internet connection and an average camera (6-8 Mega-Pixels). It performs object recognition by sending image data to Google Cloud Vision API to analyze the image and then receive the label data.

We chose to use a proprietary cloud-based object recognition



Figure 4. Testing the interaction in the environment

framework for the following reasons: (a) it requires minimum computing power on the phone; (b) has high accuracy; (c) has pre-trained multiple classification labels. The app was developed with C-sharp and uses the Unity platform to enable deployment to multiple smart-phone devices (iOS and Android). Since most of the processing is done in the cloud, the app runs also on old smart-phones with low processing powers such as iPhone 4S, which increases the accessibility of this tool.

EXPLORATIVE STUDY

We wanted to observe how designers with different expertise and — who never engaged in any kind of project that uses artificial intelligence — responded to this way of designing and prototyping with AI in the wild. For this reason, we approached a major design consultancy based in the Netherlands and recruited 6 professional designers (age 23–40, males and females) from different design disciplines, including UX Design, Digital System Design, Strategic Design, Graphics Design and Product Design. The test was conducted inside the cafeteria of the design consultancy.

Participant Number	Gender	Age	Occupation	Professional Experience in Design (Years)	Experience with AI and ML (Years)
P1	Female	28	Product Designer	3	0
P2	Female	35	Product Designer	8	0
P3	Male	26	Product Designer	2	0
P4	Male	32	Digital Designer	7	Basic Knowledge
P5	Male	40	Sr. Designer	>10	Basic Knowledge
P6	Male	23	UX Designer	1	0

Table 1. Participants Details

We first conducted baseline interviews with our participants to learn more about their knowledge of AI. Then, we introduced them the tool and explained them the purpose of our study.

We used a small demo to explain how the tool works and what they could do with it. Once they familiarized with the tool and its way of working, we asked them to generate ideas and quickly prototype concepts for a future scenario where AI is used to create a context-awareness system that detects and reacts to human interaction. The design brief was as following:

“How will you design a future workplace where AI is monitoring and reacting to your interactions with a particular context? Use the tool to explore your work-space and come up with at least one design idea that can make the workplace more efficient, fun or engaging.”

Participants used this design brief to begin experimenting with the tool. We video recorded their activities and asked each participant to document their ideas also on paper. At the end of the idea generation session, we prompted them to reflect on their experience and followed up with a semi-structured interview. We asked them questions, including: *“What was your inspiration for the designed concept?”*, *“What challenges have you encountered when designing with the ObjectResponder tool?”*, *“How did the tool help you come up with ideas?”*, *“How would you improve this tool?”*

PRELIMINARY FINDINGS

We analyzed 10 hours of video recordings of all the participants using the tool. The analysis was done in combination with direct observation of designers’ responses and a follow-up interview with each of them. All follow-up interviews were transcribed and reviewed for accuracy and textual errors. We then used the affinity diagram method to cluster the data and gave an individual code to each cluster.

Seeing from the Perspective of AI

Being able to look at the context from the perspective of a machine became a starting point for designers to directly experience how differently the machine was able to ‘see’ the world. This in-situ machine perspective seemed to enable the designer to explore a future intelligent product or service that couldn’t be thought of before.

For example, P5 was trying to set a response to a chair and the object recognition returned several labels of the carpet and floors near it. This diversion allowed P5 to come up with a different idea and envision a device that informs the cleaning ladies about how each thing in the office should be cleaned. P5 reacted: *“Although sometimes random object categories were false and frustrating, it inspired me to think more broadly about my idea and try it out with the tool”*. This seems to point to the fact that in idea generation, the diversion provided by false labels was a productive trigger for the designer to look at the same context with different eyes.

When participants instead were more focused on prototyping an idea that had already in mind, then there was frustration as object detection did not work as they wanted. P4 said: *“I had an idea which I wanted to try out, but the random categories kept appearing on the screen and it was*



Figure 5. Participant-5 trying to set a response for the object 'chair'

taking too much time to adjust the camera for the right label to be detected. I could not make it and test it out". P1 also mentioned: "Sometimes the object detection terminology was too general or different each time, and I could not prototype my idea". In the follow-up interviews it became clear that designers who already thought of an idea before exploring the context with the tool were more likely to give up than the ones who intended to use the tool for exploring ideas for possible use cases without any presumption.

We also noticed that in some cases it was difficult for a designer to follow the given design brief (i.e., 'make the work-space efficient, fun or engaging') and at the same time deal with the limitations of current machine algorithms to predict only certain object categories and not everything.

This suggests that differences in perspective between the machine and the designer (e.g., multiple possible labels) helped sustain exploration and generate new ideas, whereas the API limitations (e.g., inaccuracy or inconsistency of the classification) were experienced as frustrating, particularly in the prototyping stage. Differences in responses seemed also to be determined by the particular field of expertise of the designer. For example, P2 mentioned that: "As a product designer I have to switch my process from iterative idea generation to ideating first based on what the tool can see. And this was different for me as most of the cases I used to work with the process where I have already some initial thought of a product which I wanted to design and then I iterate over upon that product idea."

Rapid Embodied Prototyping

Finally, we observed that designers were quick to generate ideas, prototype and test them out in the actual context of use. For example, P2 had the idea to build a system that detects opened doors and nudges people to close them. Within three minutes, she was able to build the system by attaching the smart-phone next to the door and setting the message 'Close the door' (Figure 6). As another example (Figure 7), P1 observed that ObjectResponder could recognize a 'couch'. Based on this observation, she developed a context-aware



Figure 6. Participant-2 prototyping a system that alerts people to close the door by using 'glass' as label for detection

system that nudges people to use the couch for taking a mindful break during the busy schedule. Later, she was able to quickly prototype this system by recognizing the couch through ObjectResponder and setting the response "Invite someone to have an inspiring talk"

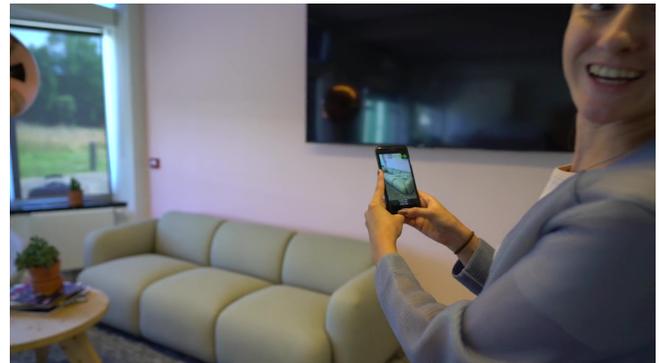


Figure 7. Participant-1 prototyping a system that nudges people to use the sofa for relaxing and having a mindful break

This embodied way of explorative ideation in the wild enabled designers to create new ideas as well as explore the consequences of their design choices while creating the context-aware system. For instance, P2 commented: "it [ObjectResponder] helps me to test prototypes and see if they work". Additionally, we also observed that while having hands-on experience with AI through the ObjectResponder tool, designers were able to critically reflect on the limitations of the AI. Understanding the limitations of the AI in the wild enabled them to brainstorm what application could meaningfully be prototyped, given the current system. For example, P4 mentioned: "the labels were helping me to know the current limitation of the computer vision technology and as a designer how can I use it to do something valuable".

DISCUSSION

Learning to design and prototype with ML is a challenge for designers. Exploring possibilities and tools for how to work with it for creating products and services is a growing effort within the HCI community [15]. Not only data scientists and HCI researchers, designers in particular are seeking ways to play and tinker with AI as a design material for innovation. Our study suggests that tools like ObjectResponder may offer designers a way to approach AI as a design material just like wood, a screwdriver or color palette, while at the same time creatively and ethically confront them with the limitations and potential biases that originate from either humans or machines. Below we would like to discuss some general considerations derived from the preliminary findings of our research.

AI as a Design Material

Designers like to use tools with which to tinker and that can adjust to their own preferences. This enables them to be creative and innovative also in the way in which they can use the tool for communicating and testing their ideas. We have observed a similar behavior with designers using the ObjectResponder tool, when they were trying to find a way to use the tool to respond to their own style and knowledge. P4 shared: *“As a product designer, I can use this tool not just to come up with an idea, but quickly prototype my idea about future social interaction”*.

Because the biggest struggle for designers working with AI/ML is having to focus on understanding how it works and what it can do, our decision was to provide designers not with a framework or a method [10] but with a tool that is easy to use and to some extent can adapt to one’s creative style. When participants used the tool to iterate over ideas, they started tinkering with how the AI would see the objects in their surrounding environment. This perception of a ‘sense’ and ‘agency’ of the AI yielded to a very different creative process, which participants seemed quite at ease tuning. The freedom of allowing designers to generate ideas over the perspective of the machine, leveraged their creative design process for designing with the AI in context. For example, P1 shared that while using the tool, she felt empowered to do whatever she wanted and not what the machine wanted.

From Design Material to Design Partner

Designers often believe that context is one snapshot, but there are a lot of layers and perspectives to it. All it is needed to access this richness and nuances, is to look at things from a different angle. Similarly, enabling designers to access and experience the unique perspective of an AI helps them realize the ambivalence of a context. We believe that to design with ML and AI, designers not only need pen and paper — or a team of software developers — but also a nonhuman perspective. The integration of human and nonhuman perspectives in the design of context-aware intelligent systems can provide an understanding of the context richer and more nuanced than the one designer could develop alone. Moreover, collaborating but also bumping against an intelligent system that is objectifying context into different layers, may enable designers to experience in-situ both human and nonhuman

biases and perhaps prompt them to consider their ethical implications.

Our findings corroborate the idea that when you let designers explore the context from a nonhuman perspective, they can augment their own creative thinking and possibly problematize initial assumptions [6]. These results are consistent with design work in HCI concerned with possible collaborations between humans and nonhumans[2][5][11][14]. Designers were able to envision ideas and concepts on the fly that would have been impossible through traditional means of design. For example, P2 mentioned that looking into the contextual information provided from the perspective of the AI allowed her to brainstorm on ideas that were popping in her mind but were not yet formulated properly. As designers will develop ‘designerly ways’ of incorporating machine perspectives, realizing the ambivalence of context, and opening up unexpected directions for ideas and opportunities they can work with, AI should be considered as a design partner rather than a simple design material.

CONCLUSION

In this paper, we have presented and discussed initial findings from the use of ObjectResponder, a tool that allows designers to use artificial intelligence (AI) to design and rapidly prototype interaction concepts for context-aware intelligent system in the wild. The tool expands previous work by introducing a simple and highly accessible way of designing and prototyping with AI in the wild by means of an average smartphone camera. In the discussion, based on the findings of our preliminary findings, and in light of similar work in the HCI space, we argue that our understanding of context changes when a designer is introduced to ‘seeing’ the world from the perspective of an AI. We also argue that — as designers will develop ‘designerly ways’ of incorporating artificial perspectives in their creative process, realizing the ambivalence of context, and opening up unexpected directions for idea generation — AI should be considered more than just another design material. Rather, it should be engaged as a design partner[6]. One limitation of this work is the limited number of professional designers with whom we tested this tool. In the future, we plan to test the tool with more designers and in multiple settings.

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