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DJ Bot: Needfinding Machines for Improved Music Recommendations

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Abstract

Modern-day music streaming services with huge music catalogs have the ability to track all of a user's interactions. Still, with all of this information on user behavior, music recommendation algorithms have little understanding of the meaningful choices that a listener makes when choosing music. To explore how to develop machine learning systems that can understand and empathize with people, we are working to merge user experience design methods with interactive technologies. We are exploring how designers can interact with people through an interactive music agent, DJ Bot, in order to elicit meaningful stories from listeners and to see how this information can inform music recommendation services.

Terry Winograd states, "Successful interaction design requires a shift from seeing the machinery to seeing the lives of the people using it." (Winograd 1997). Within design, there are a number of techniques for understanding user experience, such as contextual inquiry, surveys, and usability field testing (Kuniavsky 2003). Many of these techniques have been primarily *qualitative* in nature, echoing Winograd's focus on the lives of people using a technology. However, as products become more computationally enabled, we are able to generate and collect huge amounts of *quantitative* interaction data on how a person uses a product.

Today, this data, paired with machine learning systems, can be used to continuously update and change the behavior of a product to better meet the needs of people. For example, music services can track their listener's behavior as input for the recommendation engine that makes suggestions for songs and automatically creates new playlists for the listener. However, while machine learning based recommendation is most likely the only way to efficiently scale music recommendation for millions of users, it pushes the focus of user understanding to behavioral pattern matching (`skip song`, `like song`, `search`, `add to playlist`) rather than people's lives. While, these interactions can create good recommendations for listeners, the system has no sense of *why* someone listens to specific songs. In addition, the system often only collects data around how the user interacts with its interface. This can limit the ability for a recommendation engine to suggest songs for different contexts in one's life or to make recommendations beyond how the machine categorizes music similarity. This can also limit the system's ability to adapt to the user over time.

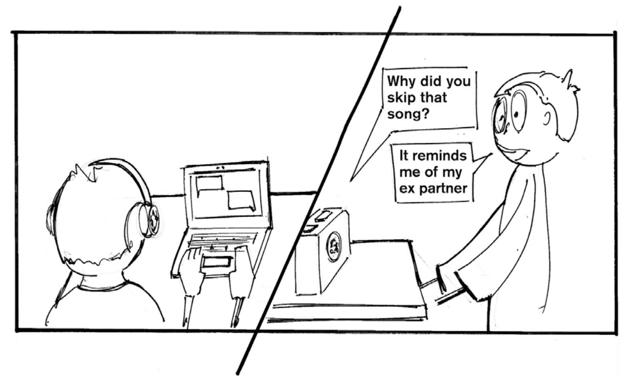

Figure 1: DJ Bot: an interactive radio that allows designers to converse with listeners around music recommendations.

In this position paper, we outline our current work-in-progress on developing systems for designers to adapt and merge *qualitative* needfinding techniques with *quantitative* data tracking and machine learning to create better music recommendations. We describe DJ Bot, an interactive, speech-based radio that allows designers to act through the machine as a means of understanding the listener. We think that this interaction can help designers develop new methods for interactive systems to elicit meaningful information about the person's relationship with music that can help recommendation systems better adapt to the listener. The goal of this work is to explore how designers can use connected products as needfinding machines and how these needfinding machines can be used to develop machine learning systems that better understand and adapt to users not just through their interactions with a product but also through an understanding of their motivations, thoughts, and feelings.

Background

Needfinding

Robert McKim defined needfinding as "a qualitative research approach to studying people to identify their unmet needs" (Patnaik and Becker 1999) and the process of needfinding has become common practice for designers today. In order to understand people's needs, designers often engage in activities that can help them build empathy for the people they are designing for. This empathy creates a connection between the designer and the person that can lead to the discovery of deeper latent needs over apparent surface needs. These latent needs are often serve as a foundation for more impactful product ideas and features.

Since empathy building and needfinding have become so important for user experience design and as new technologies change the way we interact with products, there are opportunities for research into new methods for understanding people (Wright and McCarthy 2008). As designers increasingly employ machine learning systems to alter the behavior of products, we are interested in how these systems can be used by designers to understand people. In addition, we are interested in how design methods can be used to inform new ways for machine learning systems to understand people. Overall, we are interested in exploring how machine learning systems can move beyond behavioral pattern recognition towards developing a form of empathy for the people using the product.

Music

We are focusing on music recommendation as one exploration into how design methods can influence user facing machine learning systems. Music is ubiquitous, contextual, and spans the range from individual to social. Although music is everywhere, we listen to different things in different places and have rich stories and motivations surrounding our music choices. Ethnographic studies of contemporary music listening describe how people associate meaning to their music choices. For example, Bentley, Metcalf, and Harboe (2006) describe how people manage and ascribe meaning to their music collection in similar ways to their personal photo collections. Woelfer and Lee (2012) explored the role of music in homeless young people's lives using a design sketching activity around creating one's personal music player. This elicited deep and meaningful stories from many teens and created a rich picture of their relationship with music far beyond the play count of songs in their iPods.

As online music services grow in popularity, the listening behaviors of people are also changing (Leong and Wright 2013). Music is now more accessible than ever, but also more personal. With the advent of large databases of cloud-based music libraries and on-demand access to almost any music available, many services have relied on recommendation engines to aid listeners with ready-made playlists. Often, these playlists are algorithmically generated based on similarity-preferences derived from user ratings of music when the listener begins using the service (Rashid et al. 2002). Over time, these systems track the listener's behavior, compare their plays to similar users, and update their probable preferences to suggest new music. Still, even with huge amounts of user data, it can often be challenging to truly understand the listener's motivation for their music choices. For example, in an analysis of six years of listening data from 310 user histories, Baur et al. (2012) found that seasons and music novelty were the largest factors defining listening habits. Although these two factors highlight the importance of context on listening habits and suggest that people enjoy new music, they do not address *why* listeners behave in these ways. We believe that there are many opportunities for designing interactive music services that can elicit the type of meaningful information that designers and ethnographers often collect and that this information can be used to better seed music recommendation algorithms.

Designing Interaction for Eliciting Meaningful Information

In our previous work, we have used interactive devices as tools for designers to better understand people. Within the space of Human-Robot interaction (HRI), we have explored and designed different interactions so that robot tutors can elicit stories from students while they are learning electronics (Jung et al. 2014; Martelaro et al. 2016). These interactions involve the robot being interested in the student and asking questions outside of the learning task. We have found that although these interactions were simple and programmatic, akin to systems like ELIZA (Weizenbaum 1966), the stories they elicited often helped us as designers to understand the students at a deeper level. While the robot interactions can be likened to Gaver and Dunnes *cultural probes* (1999) and Hutchinson et al.s *technology probes* (2003), these insights were found during the moment of interaction with the robot, rather than before or after an interaction. This work has lead us to further explore how interactive devices could be used to do in-the-moment needfinding through the use of interactive devices.

We have extended this idea of designers conversing and understanding people *through* interactive devices in the automotive context. We have developed and tested a system, WoZ Way, to allow remote designers to prototype interactions and observe drivers as they are on the road (Martelaro and Ju 2017). Using live video, audio, automotive data collection, and Wizard-of-Oz speech interfaces, we are able to allow designers to act as an intelligent agent in order to explore the possibilities for what an in-car agent could do. Through recording these interactions, we can inform the future design of these machines, highlighting what data may be useful and what aspects of the interaction are important for machine learning systems to address. Additionally, the designer's interaction can help to bootstrap a future learning algorithm.

DJ Bot: Exploring Elicitation for Music Recommendation Services

Building upon our previous work, we are now looking to explore how design methods can be used to inform machine learning algorithms, specifically for music recommendation. Music services are one current product where user experience is heavily influenced by machine learning systems. Additionally, as music is deeply meaningful and personal to people, we believe that methods for empathy building and needfinding can be designed into interactive devices and help recommendation systems to create a richer understanding of a listener. We have modified our WoZ Way system to

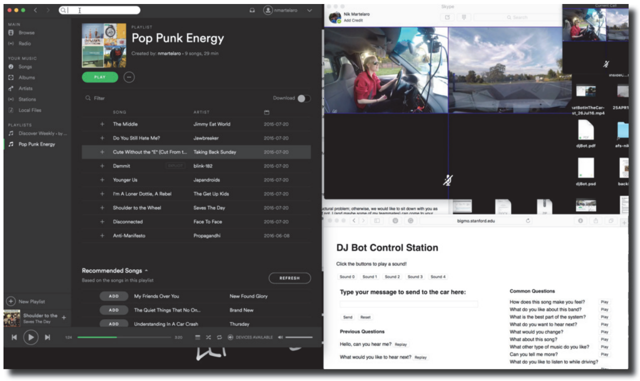

Figure 2: Screenshot of the Wizard's DJ and control interface during an on-road exploration.

allow for remote control of a machine learning based music application and Wizard-of-Oz speech interaction between a remote designer/DJ and listener. This interactive agent, DJ Bot, allows a designer to actively explore what new interactions might provide insight into the listener's choices. The designer can also interact with the automatically recommended music and playlists, allowing them a hands-on interaction with the recommendation algorithm's choices. This allows the designer to qualitatively explore how the user reacts to and engages with recommendations. In addition, the remote nature of the system allows designers to interact with listeners in their own contexts, for example, their home, work, or even in their car as shown in Figure 2.

We intend to use these interactions and the information that is collected to explore what can be used to augment currently available recommendation systems. For example, these interactions can help to overcome the "cold-start problem" (Eck et al. 2008) by helping to generate an early list of music preferences. These interactions can also help to explore how a music recommender can recalibrate when the listener is unhappy with the recommendations or can help to develop an understandable explanation for recommendations, both issues that have been brought up in user evaluations of contemporary music services (Lee and Price 2016).

Discussion

Overall, our goal in this work is to explore how interactive devices can be used by designers to inform the design of machine learning systems. Our research blends modern design methods with emerging, data-driven technologies in order to inform the design of systems that not only recognize user behavior but also allow designers to understand the lives of people using these systems. With the designer in-the-loop, they are also able to gain a more tacit understanding of how a machine learning based system might sense the world. This can help to inform the designer's decisions on what data might be important for the algorithm.

The implications of this work have the potential to influence the design of recommendation engines beyond music, such as for product recommendations or other types of media. This method of interacting through the machine may also help in developing new design patterns for conversational interfaces, where systems can ask their user questions in order to learn more about them. Through understanding the process that designers take while interacting through the machine, we may be able to generate methods for allowing machines to uncover latent needs on their own.

Author Biographies

Nikolas Martelaro is a Ph.D. student in Mechanical Engineering at Stanford University's Center for Design Research DesignX Group. He has extensive background prototyping tangible, embedded interactive systems. His current work focuses on how computationally-aware physical products can elicit meaningful interactions with users and how these products can relay those experiences back to designers.

Wendy Ju is Executive Director of the DesignX group at Stanford University's Center for Design Research and Associate Professor of Design at the California College of the Arts (CCA). Her current research in the areas of physical interaction design and ubiquitous computing investigates how implicit interactions can enable novel and natural interfaces through the intentional management of attention and initiative.

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