MAX YI REN RESEARCH STATEMENT

Design research has long encompassed a duality in its methods: In mode one, we advocate design automation by advancing modeling and optimization techniques; and in mode two, we cherish human intelligence for bringing innovations to existence.

Most researchers and practitioners agree that the two modes are complementary, since it is always a human being that architects a design, e.g., how space is laid out in a building; and it is always the machine that fine-tunes the performance of a human creation. Without machines, we can hardly optimize; and without human, the machine is left with infinite design possibilities to search from. The fusion of the two modes is so desired yet remains a challenge, as in the ever-complicating design world, searching for good solutions through multiple disciplines is never a smooth experience for either machines or human.

Is there a way, then, for us to combine the two modes so as to design both rationally like a machine and smartly like a human? This is an audacious question to ask, yet, with the growing machine learning abilities and human-machine interactions, answering the question is now probable and intriguing. The solution, in my vision, lies in a design automation mechanism that requests, organizes and learns human intelligence. For example, an algorithm that searches for the optimal configuration of powertrain components, e.g., engine, motors and planetary gears, might be able to improve itself by learning from existing patents; or an artificial car styling designer can tune its creation by tracking trends in human-submitted designs.

Two major topics on human-powered design automation are presented in the recently funded NSF grant that I co-authored, with the title "Creativity through Collaborative Human-Machine Interactions: A Formal Approach to Design Crowd Sourcing":

(1) **Interactive design as a data collection method:** In order to train a machine for a specific design task, we need to first collect human-created designs (sketches, CAD models or other forms), performance associated with these designs (human evaluations and engineering simulations) and possibly participant demographics which helps to group tastes or ideas. While crowdsourcing platforms abound, design creation is a demanding task and collecting such information is challenging. My dissertation work proposed to address this challenge by using human-machine interactions appealing to users. Specifically, I created an online interactive car modeler that iteratively refines a 3D car model based on user feedback. The application helps both normal users to easily create 3D models and express their ideas and also for us to collect data and learn from them the preferences of people.

    Besides all practical issues related to the design of human-machine interactions, my major research goal here is to improve the efficiency of the learning mechanism during an interaction. After all, human beings lose attention to an interaction if it takes too long. My research tailored modern machine learning techniques to learn user preferences based on their choice responses on design alternatives and propose new designs more likely to fit their needs [1]. In a special case where only finite design alternatives exist, I showed that a theoretically-proved strategy used for the "20 questions" game can be adjusted to efficiently elicit the most preferred designs of users through interactions [2]. In addition, the topic of how cumulative knowledge from a crowd can help improve the learning algorithm is also discussed [3]. It should be noted that the focus here is on active learning as oppose to passive ones such as those in recommender systems.

(2) **Learning to improve design heuristics:** When a set of designs are collected and evaluated, the

keen questions to ask are then: (1) Can we learn which designs are better and why? If yes, (2) then can we create new designs automatically or even optimize one?

Learning from people has always been a challenge due to noisy human responses. In some cases, this is due to people's different level of understanding, e.g., whether people can evaluate building layouts correctly depends on their experience in this design topic; in other cases, it could be their own preferences that lead to different evaluations on the same design. For example, my previous study showed that when presented a pair of car designs and asked "which car looks safer", half of the participants voted for the "stream-lined" design while the other half for the boxy one [4]. Such differences in knowledge or preference could be explained by demographic background of people or identified through their social interactions including evaluations on other design topics. The key here is the development of learning algorithms that can extract high-level information to better explain the observations from the massive joint data of designs, people profiles and interactions. Existing feature extraction methods such as sparse-coding and restricted Boltzmann machines will be investigated. It should be noted I collaborate with marketing researchers on this topic as it is closely related to the development in modern market prediction methods.

Learning from engineering data, on the other hand, has a different flavor of challenge. A specific problem under investigation is the optimal design of a hybrid powertrain architecture. For a system with two motors and two planetary gears, my previous research showed that a thousand feasible configurations (driving modes) exist [5]. As a powertrain may consist of multiple configurations (such as in Chevy Volt), this large number of candidate configurations will make the search of an optimal powertrain intractable. Existing studies often restrict the space for architecture search based on human experience and rules, excluding chances for discovering innovative designs. Learning from existing configurations to form better search heuristics is therefore desired in such engineering tasks. While the idea already exists, e.g., in response surface methods, the particular difficulty here is that configurations are often represented as graphs (e.g., a powertrain configuration is commonly represented as a bond graph). Successful learning from graphical data requires a problem-specific extraction of graph features, on top of the large collection of graph properties. Therefore the tasks of learning from human evaluations and engineering data shares the same core challenge.

To summarize, the long term goal of my research is two-folded: First, I would like to push design automation to the next level by improving learning ability of the machine and management of human intelligence; Second, I want my research to lower the barrier of design activities and encourage more people to contribute their talents.

References

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