Learning Aesthetic Knowledge with Designer-Like Thinking and Interactive Machine Teaching

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Abstract

Aesthetics is a crucial aspect of design that plays a critical role in the creation process and customers' perception of outcomes. However, aesthetic expressions are highly subjective and nuanced. It often relies on designers' experiences and many trials and errors to get it right. Our research first investigated how designers and artists curated aesthetic materials and utilized them in their daily practice. Based on the result, we applied Langley's human-like learning framework to develop an interactive Style Agent system. It aims to learn designers' aesthetic expertise and utilize AI's capability to empower practitioner's creativity. In this paper, we used typographic posters as examples and conducted a preliminary evaluation of our prototype. The results showed that our system provided a modular structure for effortlessly annotating users' subjective perceptions and making the visualizations easy to interpret through performance. Overall, it acts as a facilitator to help enhance their own aesthetic awareness and empowers them to expand their design space.

Introduction

Artificial intelligence (AI) is increasingly utilized as a coworker and integrated into people's daily practices and lives. While the advent of large language models and deep learning shows promising applications in many domains, they often fall short of grasping the subtleties and understanding users' emotional intentions (Artist 2023). Artists and designers' primary work is to evoke specific emotions or moods. In practice, they often spend significant time experimenting with many ideas to create aesthetic qualities that match the clients' or target customers' tastes. However, it often relies on designers' experiences, tacit knowledge, and many trials and errors. For instance, when Tyler Hobbs created the Haecceity series of generative artworks, he found it very challenging to examine the 950 images generated by the algorithm developed by himself (Hobbs 2014). He looked at each of them and studied the best images' compositional strength, balance, rhythm, and quality of detail. After spending a significant amount of time with trial-and-error examination, he narrowed the images down to 24 and chose 7 of them, which complement each other, show the range of the program, and generally work as a series.

Aesthetics is an essential aspect of design that plays a critical role in people's perception and experience of products, services, and environments. Although recent generative AI applications (e.g., Dall·E or MidJourney) show an impressive improvement in the outcomes' quality, the dominant prompt engineering is not intuitive for designers to steer the ideation process with particular aesthetic visions or intentions. It was also found that AI-generated content shared obvious similarities and lacked diversity compared to human-generated outcomes (Dell'Acqua et al. 2023). Perhaps this is because the existing AI systems lack knowledge of aesthetics and subjective feelings. As a result, designers still need to examine vast amounts of generated outcomes and adjust their inputs by trial and error. Those reflections triggered us to ask: *What if the designers can teach AI what aesthetic qualities entail with examples they collected and/or created?*

Due to the subjective nature of the aesthetic qualities, Langley's human-like learning framework (Langley 2022) could play a significant role in acquiring designers' knowledge and using the know-how to support their creativity process. In this paper, we summarized how we applied some characteristics in developing the Style Agent system.

System Overview

The interactive teaching interface was developed with a modular structure based on Kansei Engineering (Lévy and Yamanaka 2009) methodology. Powered by interactive machine-teaching techniques (van der Stappen and Funk 2021), the system can learn the essence of designers' aesthetic expertise and build the user's model as a computational representation of their design style (see Fig.1B). For instance, the Concept Aviation Vectors (CAV) method (Kim et al. 2018) can generate mathematical functions to represent the aesthetic qualities in multidimensional design space. Furthermore, we use the user's CAV model to predict the aesthetic perceptions of new design examples (see Fig. 1C). This design space can help designers to define a concrete direction for a given assignment and examine the design references to examine critical design parameters and how they might affect particular aesthetic qualities. In this study, we used the poster design as a medium to investigate its application and efficacy.

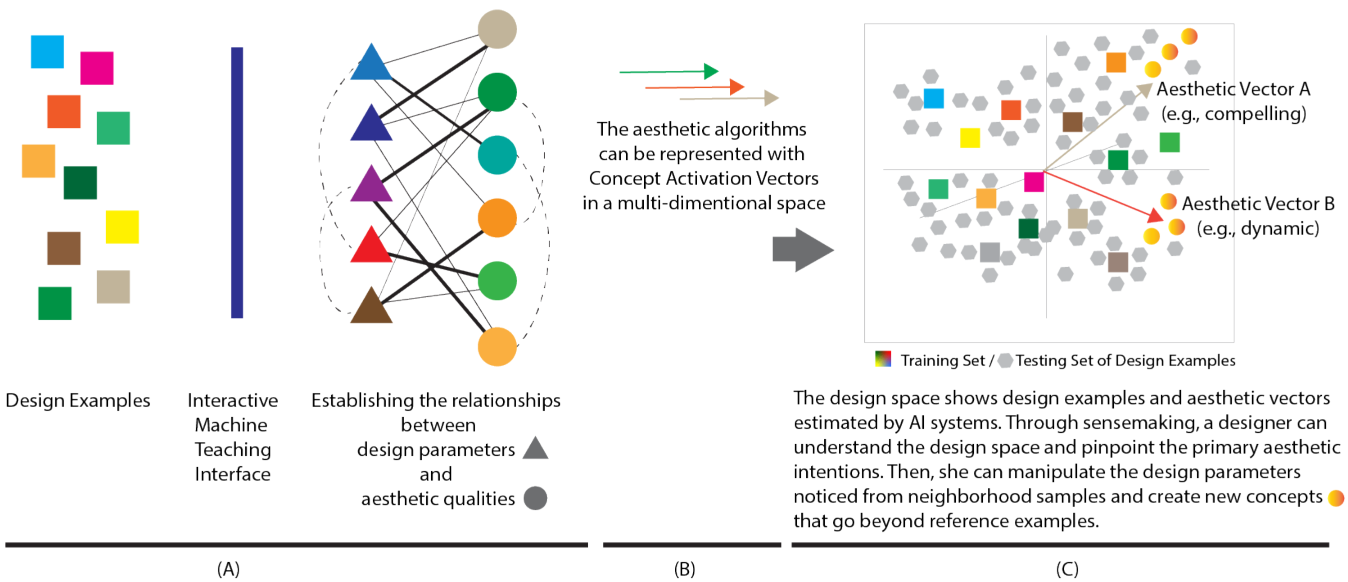

Figure 1: The framework of this research project: (A) Developing an interactive machine teaching interface for engaging designers to teach AI systems with design examples. (B) Using machine learning techniques [e.g., Concept Activation Vectors (Kim et al. 2018)] to transform aesthetic algorithms into computational forms. (C) Visualizing the design space with examples and aesthetic vectors generated from B. Designers can not only use the map to identify new opportunities but also manipulate the noticed design parameters (such as shapes, colors, or materials) to experiment with creative designs for conveying certain aesthetic qualities (e.g., expressing energetic and dynamic feelings with balanced quality).

Modular Cognitive Structure

In many designers' practices, they constantly collect inspirational objects or images even though those materials do not serve their current projects (van der Burg et al. 2023). Our Style Agent system aims to transform those personal collections into the system's knowledge and use it to inspire designers' creation when they want to create something with particular feelings. By using Kansei Engineering (Lévy and Yamanaka 2009) methodology, we design the interface with bipolar semantic adjectives (Chuang, Chen, and Chuang 2008) (see Fig.2). A designer can easily use this modular structure to annotate their perceived aesthetic qualities on given artifacts. The data was then processed with Google's AI and Mood Board search (Google 2022) to build machine learning models for each aesthetic scale. Our system also provides flexibility for users to acquire personal databases in a piecemeal manner. A user can decide when to annotate the collected materials and add or remove aesthetic adjectives according to their relevance.

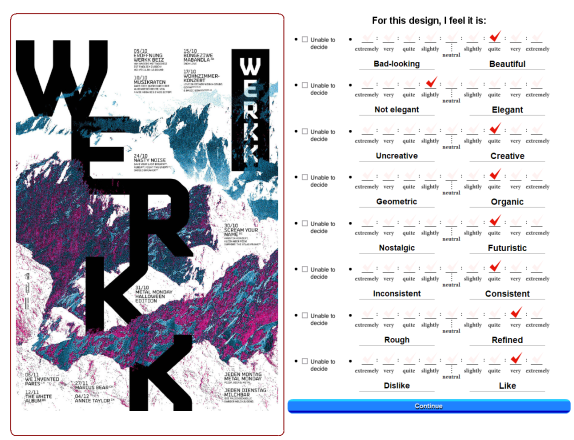

Figure 2: The interface for a designer user to annotate their aesthetic perceptions on given artifacts.

Compose the Knowledge During Performance

After our system processes the annotated data and builds the user's preference models (Google 2022), our system will use those models to estimate their aesthetic values on a preselected dataset of artifacts and visualize the results with two types of representations. One is the two-dimensional distributions on each aesthetic scale (see Fig.3). A designer can easily browse various artifacts and select the ones they find inspirational to their current tasks. In addition, they can also edit their annotations to correct or update the system's knowledge. This has an important implication in design practice because subjective judgment is dynamic and highly influenced by the contexts (van der Burg et al. 2023). The other visualization is a three-dimensional design space with artifacts (see Fig.4). This design aims to give designers an overview of all the existing examples and help them to define the design direction by positioning their vision on the map. To avoid the common frustrations of AI systems due to their inaccurate prediction and unclear explanations (Jeon et al. 2021), we purposely incorporated user-in-the-

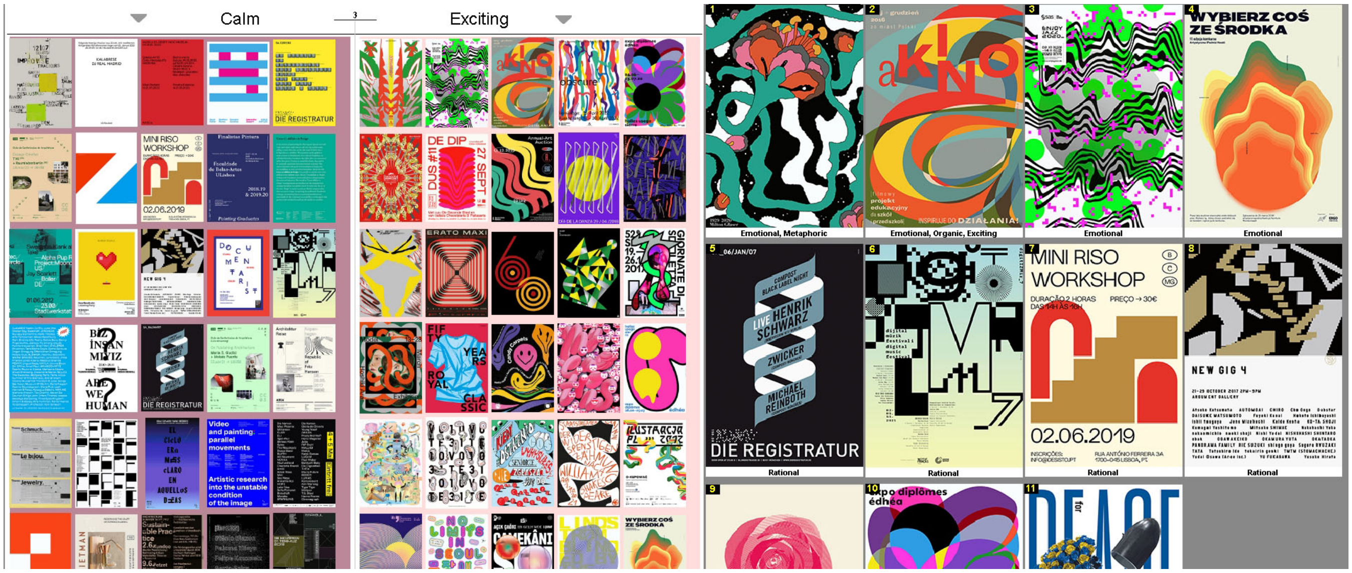

Figure 3: The interface of the two-dimensional visualization. A user can click the adjectives to browse the exemplars of a particular aesthetic scale (i.e., Calm-Exciting shown on the top). He/she can also curate useful examples by clicking the thumb stimulus image to pin a bigger version on the right panel. The system will add the adjective to the note shown at the bottom of the image. The user can edit the note to re-teach the machine's knowledge.

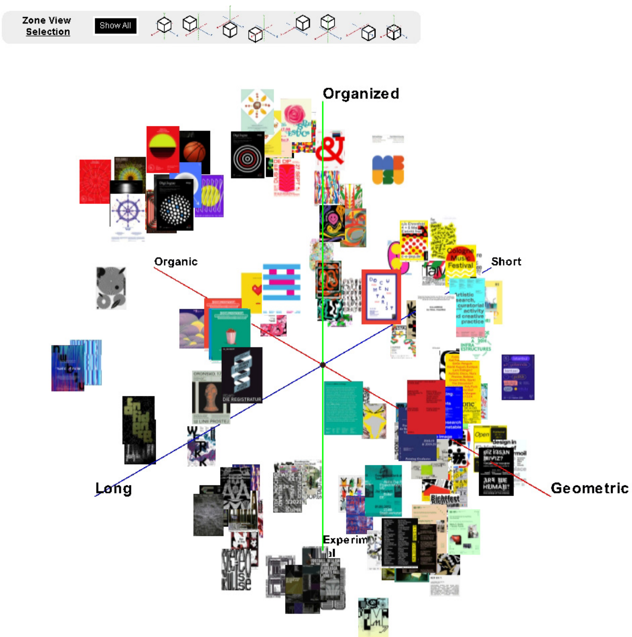

Figure 4: The interface of the three-dimensional visualization. A user will analyze the distribution of artifacts and define the axes as meaningful interpretations of the design space. Similar to the 2D interface (Fig.3, a user can drag the stimuli to a new location to re-teach or update the machine's knowledge.)

loop interactions by guiding them to interpret and define the axes with their words. Although this might increase a user's cognitive workload in analyzing the design space, we believe this interaction can help to capture their tacit knowledge through performing this decision-making task during the design process.

Preliminary Evaluation and Results

To evaluate the performance, we conducted a user study with six designer participants randomly divided into two groups. Group 1's participants helped use our interactive interface to rate 156 poster stimuli separately with 30 bipolar adjective scales (see Fig. 2) according to their perceptions. By processing the data using Concept Activation Vectors (CAV, a machine learning program (Google 2022)), the system generates models to predict the aesthetic qualities of other one thousand design examples not included in the annotation task. Then, our Style Agent system will use the machine's prediction values to visualize each stimuli's location in a two- or three-dimensional design space (see Fig. 3 and 4 respectively). Both groups' participants are asked to browse and interpret the design space, and use the insights to define a design directions for creating a new poster in 20 minutes followed by interviews. We collect quantitative and qualitative data to assess the system's performance. In the following section, we used different annotations to help readers understand a particular participant's feedback from a specific group. We used PA-C to represent the three participants of Group 1, and P1-3 for Group 2's participants.

Firstly, we investigated the correlations between Group 1 participants' ratings and the CAV's outcomes. Unsurprisingly, the initial CAV data shows diverse results. In the PB's data, we saw the predicted results all have significant correlations on the 30 scales, and there are only less than one-

Figure 5: Posters designed by participants with our Style Agent system. Group 1's participants completed both the data annotation (Fig.2) and poster design tasks. Group 2's participants only did the design task by using the visualization made based on Group 1's data. Although their designs all looked similar to the existing examples, most participants were satisfied with the aesthetic expressions embodied in the outcomes. It shows that our *Style Agent* system could facilitate a user to create initial ideas with a particular aesthetic quality in 20 minutes. They can have a longer time to fine-tune the outcomes.

third of significant cases in the other two participants' data. This indicates that the user-in-the-loop interaction design we incorporated in the visualization (see Fig.3 and Fig.4) could play an essential role in facilitating users fine-tuning the learning. Furthermore, after completing the poster design assignment (see Fig.5), most of the participants said that the visualization function of the system "helps me express myself" (PC) and helps interpret the design style, "I feel that it visualizes a feeling I have in my mind" (PC). One participant said, "...can refer to this when I think about the design style" (PA). It also helps them understand their own design style and serves as a reference for positioning their own work "because I didn't know what my own style was like before, and if I put my work on it, I can see where I am" (P3).

The system also helped participants establish the design style of the poster: "I think it helped me more to establish the style quickly in the early stage" (P2). The semantic-differential adjectives embedded in the system allowed the participants to get more suggestions and even to learn from them, "... It's not just the part that I want, but also the opposite part, that is...what kind of situations I want to avoid in my poster, it's also there" (PC). The participants thought that the bipolar adjective scales in the system could also be used as a search keyword, "... afterward when I go to search for such similar posters, I can also add this as a keyword into it" (P1).

Overall, our study shows that a small number of data could achieve good performance through the interactive teaching and visualization system developed with human-like learning characteristics.

Acknowledgment

We collected and used high-quality posters from the typographicposters.com website. They are all under CC by-nc-nd 4.0 license. We thank all designers who published their posters on the public platform.

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