Minimally Juxtapository Tasks as a Co-Creative Systems User Study Method

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Abstract

Conceptual design is an exploratory stage in the creative design process that is challenging to augment with computational techniques. Part of this challenge comes innately from the flexibility and reframing-centric nature of the task itself, but an equal contributor is the trouble of measuring, standardising, and working with conceptual design in experiments. We propose a model for studying conceptual design in co-creative systems based on minimally juxtapository tasks (MJTs). In this paper we detail a case study of conceptual designing with AI-based art tool, ArtBreeder, using our new task format. Through MJTs, participants engaged with features of ArtBreeder and reflected upon its capacity to assist them. We performed thematic analysis on post-task interviews to derive a series of themes for use in better understanding user attitudes and behaviours. The findings help frame the shortcomings of existing conceptual exploration tools, validating the MJT method.

Introduction

Conceptual design is an important stage in the design process (Pahl et al. 2007), exploring not just possible designs but constraints, requirements, and interpretations of the brief that define the emerging space of possible designs (Maher, Poon, and Boulanger 1996). Conceptual designers enact the prototypical exploration of forms, motifs, and constraints in early phases of designing. At present, there have been few computational tools used in conceptual design compared to other design activities. It appears that conceptual designing is one of the last aspects of designing to be transformed by computational tools – likely due to the requirement for representational flexibility and the regular re-invention of requirements.

Recent research on generative machine learning may offer an opportunity to develop a new form of computational technique that is more well-suited to the conceptual design stage (Maher, Poon, and Boulanger 1996). However, given the unique nature of conceptual design, no well-validated methods for exploring the efficacy of such techniques exists (Lawton et al. 2023a). In this paper we propose a generalisable task format as a step towards standardising research in co-creative systems for conceptual design. Our task format, *minimally juxtapository tasks*, or MJTs, focusses on finding the simplest possible task that incorporates traditionally opposed concepts. Tensions and juxtapositions are common antagonists in conceptual design, and their confrontation is one known driver of creativity and innovation (Dorst 2015). We define the MJT concept, then present a case study in which a generative machine learning system designed for an artistic domain is re-purposed to conceptual design tasks through their use. This study lets us explore how designers interact with tensions and juxtapositions that occur in much more complex tasks, but in the simplicity of a short user study. We believe this method offers a glimpse into how to best design future conceptual design tools.

ArtBreeder (screenshot shown in Figure 1) is a visual image synthesis tool used in the concept art domain, where artists working on games, films and other media develop early concepts for their characters, environments, and scenes. We detail a qualitative study in which 11 participants used ArtBreeder to generate character faces based on MJT-style prompts, followed by an interview exploring how the tool affected their creative process. We then conduct a thematic analysis of the results to explore the potential for minimally juxtaposed tasks for conceptual co-creative AI.

Related Literature

Conceptual Design is a preliminary stage in the design process for exploring possible solutions, requirements, interpretations and constraints in response to the design problem (Bentley and Wakefield 1997). Conceptual design involves re-representing and reformulating designs. The iterative reformulation of conceptual design can be interpreted through an exploratory co-evolution model (Maher, Poon, and Boulanger 1996; Wiltschnig, Christensen, and Ball 2013), where the problem space and solution space modify one another and refine both the design solution and design requirements.

Recent advances in generative machine learning techniques have enabled neural networks to synthesise artefacts that are indistinguishable from human-generated examples in many domains, at least under certain constraints (Bessette, Fol Leymarie, and W Smith 2019). These advances have been applied to conditional image synthesis (including sketches (Di and Patel 2017), text-to-image synthesis (Zhang et al. 2017), text-guided image editing (Li et al. 2020) and style transfer (Gatys, Ecker, and Bethge 2016).

Examples of how these techniques have been applied to creative domains can be found in DALL-E (Ramesh et al. 2021), CLIP (Radford et al. 2021), Stable Diffusion, and Sketch2GAN (Wang, Bau, and Zhu 2021). These forms of cross-modal synthesis lend to an important aspect of conceptual design: the re-representation of designs.

Research in creative systems has described a continuum of roles among humans and creative systems: creativity support tools, co-creative agents, and fully autonomous creative AI. Creativity support tools assist human creativity but do not necessarily use AI to do so. Fully autonomous systems generate creative artefacts themselves, with the involvement of humans limited to down-stream evaluation and curation of their output. Co-creativity, the focus of this paper, is instead a collaboration between humans and computers to develop shared creative artefacts (Davis 2013). Notable co-creative systems include Sentient Sketchbook (Liapis et al. 2013) in game design, the Creative Sketching Apprentice (Karimi et al. 2019) and Reframer (Lawton et al. 2023b) in sketching, EvoFashion (Lourenço et al. 2017) in clothing design, and a huge variety in the domain of music (Ford et al. 2022).

Minimally Juxtapository Tasks (MJTs)

We developed MJTs as a way to explore conceptual design in user studies through simple tasks, based on the question: how simple can a study task be while still retaining analogous enough to a real-world design problem that the appropriate cognitive machinery must be recruited to solve it? Our proposed answer to that question coalesced into the MJT, which can be defined as:

> *A creative brief, typically described in a single sentence, that requires imbuing an artefact with two concepts that are conceptually, affectively, or otherwise significantly opposed.*

The juxtaposition at the heart of these simple tasks makes for a creatively interesting brief, requiring designers/artists to negotiate ideas that would stereotypically be opposed. For example, in our face-generation case study using ArtBreeder, the four tasks were to depict:

- “A grizzled veteran with a heart of gold.”
- “A sweet senior citizen with a wild side.”
- “A detective with a music career side hustle.”
- “A zombie politician.”

Case Study Methodology

As an initial exploration of the efficacy of MJTs in a real-world co-creative systems context we used the popular ArtBreeder web-based co-creative platform as the subject of a case study. ArtBreeder[1] is a web-based platform created by Joel Simon for artistic exploration and image generation that uses machine learning techniques to create and evolve digital art. It uses a combination of generative adversarial networks (GANs) and autoencoders to manipulate images.

[1]www.artbreeder.com

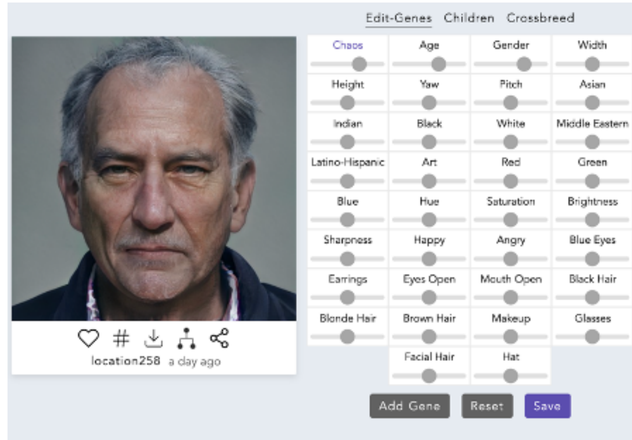

Figure 1: An example of the ArtBreeder system, showing the Edit Genes feature for a face.

We investigated the efficacy of ArtBreeder on conceptual designing using MJTs with 11 user participants. For the first three tasks, one of the system’s features was used: (1) Edit-Genes, modifying distinct image attributes such as eye colour or age, through sliders; (2) Children, mutating a selected image; and (3) Crossbreed, blending two images with content and style sliders. In the final task they used all three.

The participants were practicing designers from a variety of disciplines, six women and five men. Tasks were conducted via remotely recorded video calls and screen sharing due to the ongoing pandemic. Each participant was given four task prompts, three paired with a particular feature of the ArtBreeder platform, and the fourth where they were able to use all features concurrently. Participants were given 10 minutes to create a face for each prompt.

The task to design faces was selected for several reasons: faces are a rich creative domain and are the subject of many creative works, juxtapositions feature heavily in those works, ArtBreeder has a dedicated portrait model, and the domain does not require prior design expertise. We followed a mix between a semi-structured post-task interview and a concurrent think-aloud protocol: during each task participants were encouraged to describe what they were thinking and doing, as well as prompted if they remained silent. After each task participants were asked a few open-ended questions about their satisfaction with the result, creative self-efficacy, and the experience of using ArtBreeder.

The during- and post-task dialogues were transcribed, then coded using an inductive thematic analysis process (Braun and Clarke 2006) in NVivo 12[2]. The first round of coding sorted participant phrases into distinct themes, which were then organised into higher-order themes.

Results

272 participant quotes from our 11 participant interviews were sorted into 10 themes, which were in turn organ-

[2]https://lumivero.com/products/nvivo/

ised into three higher-order themes: Discovery and Open-endedness, Control and Intent, and Expressibility.

Table 1: Themes in "Discovery and Open-endedness"

Theme	Description
Design goals and strategies	Desired outcomes and intentions at the task and subtask levels, and the participant's means of achieving these desired outcomes
Search behaviour	Cognitive and creative process in finding and navigating tools and content that appropriately satisfy their desired outcome
Unpredictability and surprise	Unexpected and surprising behaviours, output, interactions, and performance of ArtBreeder systems and functions and to what degree they help or hinder the participant under different circumstances
The "black box"	Lack of understanding or intuition of the algorithms or functions in ArtBreeder, how the system works

Discovery and Open-Endedness

The Discovery and Open-endedness higher-order theme (see Table 1) represents behaviours and qualities relating to predictability, surprise, searching, novelty, exploration, non-fixation, associativity, fluid representations and re-representation. This higher-order theme involves the process of finding solutions, exploring the system and interacting with it, navigating through the index of user-generated content, and selecting the right candidate image from a neighbourhood of similarly appropriate images.

Table 2: Themes in "Control and Intent"

Theme	Description
First impressions	Immediate response to the ArtBreeder content, layout, community, functions, and interface - and any associations they make with other tools
User experience	Reflections on the interface, layout, and design choices and to what degree they interfere or support the participant's goals
Sense of control	Perceived level of influence over granular features and the final images produced

Control and intent

The Control and intent theme theme (see Table 2) represents the system's capacity to afford user control, the minimum predictability to achieve intent, the user experience of the ArtBreeder platform, and preconceptions towards the ArtBreeder website and community. Control and intent involves the specific properties users interact with directly or indirectly, specific features and components of ArtBreeder, and more generalisable beliefs about co-creative AI systems.

Table 3: Themes in "Expressibility"

Theme	Description
Creative self-efficacy	To what degree ArtBreeder has enabled them to express their creative intentions, or whether their cognitive experience of creativity has been augmented
Sense of authorship	Perceived ownership, level of input and directedness of the final output
Sense of collaboration	Perception of interaction and co-creation with an intelligent agent or with other users on ArtBreeder

Expressibility

Expressibility (see Table 3) represents the potential for participants to achieve creative reward and agency, impressions of authorship, and a sense of collaboration with both the ArtBreeder system and community. Participants expressed concerns over their control and authorship of artifacts made in a system that is largely unpredictable, difficult to understand, has varying levels of direct control, and the level of creative self-efficacy afforded by the system.

Discussion

Our case study highlighted both technical and design considerations related to how we might interact with intelligent creative design systems that possess some level of autonomy of intent and action. We discuss several of those considerations here, but overall our study emphasises the efficacy of MJTs as a model for co-creative systems research. Despite their simplicity, our tasks that involved a tension between concepts – one that is not easily facilitated by the system – required our designers to apply their human-level understanding and creativity. We observed users switching between reframing the problem and trying to solve it, reverting back to previous design states, and exploring serendipitous options afforded by the ArtBreeder tools. While our study was not controlled (in that we did not ask some users to perform tasks without essential conceptual juxtapositions), we can say from years of experience in co-creative systems and generative AI that we do not typically observe comparable levels of design-like thinking in other tasks of this simplicity. We believe accordingly that minimally juxtapository tasks are a promising approach for future co-creative AI studies.

In our ArtBreeder study, despite the simplicity of our tasks, the juxtaposition they required made them "creatively interesting" for our users, leading to a number of insights about co-creative systems. Users found the black box nature of ArtBreeder both compelling and frustrating, reflecting larger trends in artificial intelligence research: the need for explainable and interpretable models using techniques that make complex systems more transparent, communicative, and predictable (Llano et al. 2022; Zhu et al. 2018).

(a) Task 1: "A grizzled veteran with a heart of gold" by Participant 4

(b) Task 2: "A sweet senior with a wild side" by Participant 4

(c) "A detective with a music career side-hustle" by Participant 9

(d) "A zombie politician" by Participant 9

Figure 2: Sample participant-made images in each of our minimally-juxtapository tasks

Our users also experienced an expectation mismatch with ArtBreeder, as its resemblance to existing image manipulation tools made them apply their existing mental models from that domain. These mental models led them to expect much more direct control and fine-grained interactions, which would likely not have been the case if we had used a prompt-based or other more-abstract interaction paradigm. This is much broader than ArtBreeder or MJTs: as creative tools gain intelligence and autonomy and the line between tool and agent blurs, it is likely that existing expectations and mental models will be violated on a regular basis. This is not a bad thing, as new interaction modalities always require new interface paradigms, but it highlights the importance of the HCI work that must accompany the development of co-creative systems (Kantosalo et al. 2020).

The scope of the present study concerns generative co-creative systems; however, we believe that it is possible that MJTs could be of use in other computational design contexts. (Hayes et al. 2011) provides a retrospective summary of other forms of artificial intelligence in various design domains. It details research into reasoning systems that are model-based, knowledge-based and case-based; knowledge-representation and reasoning; generative design; and various research challenges and directions adjacent to the present study. In any design task where humans and intelligent agents collaborate, there is a potential for MJTs to be a useful framework for experimental design.

Even within generative co-creative systems, there is a wide variety of roles and modes of interaction. COFI, a framework developed on the study of 92 co-creative systems, identifies three fundamental interaction models: 1) generative agents that follow the user's directions, 2) mixed-initiative agents that work alongside users on a shared product, and 3) advisory agents that both generate and critique the user's creative product (Rezwana and Maher 2022). Artbreeder is an example of the former: it follows the user's directions, and the user must interpret the MJT's essential contradiction on their own. In a more mixed-initiative co-creative system like Reframer (Ibarrola, Bown, and Grace 2022) or the Drawing Apprentice (Davis et al. 2016), that creative responsibility (of somehow resolving the juxtaposition at the heart of the provided task) would be shared. This may stress the generative capacity of some systems, potentially leading to situations where the user must step in and take back control (as in our study), which could be a useful proxy for more-complex design tasks. A similar story may hold true for more advisory/critical agents, whose evaluative mechanisms may struggle in tasks with conflicting requirements.

Conclusion

We have conducted a user study designed around minimally juxtapository tasks (MJTs) to investigate the capacity for co-creative systems to support the solution to realistic conceptual design problems in the domain of concept art. The negotiation between conceptual tensions that occurs in early-stage creativity is critical, and surfacing it in user studies will hopefully attract additional attention to this underaddressed component. Our analysis shows that, even with these very simple tasks and a relatively simple (even outdated) co-creative system, a significant degree of nuance was achieved by our users in their design tasks. This suggests the potential of MJTs as a framing for experimental design in co-creative contexts. Our study also elicited a number of themes that show the challenge of designing future co-creative systems. Resolving some of these of these challenges will draw on the AI domain, namely explainability and shared goals and meaning, whereas others will draw on HCI and computational creativity, such as how to design interfaces and interactions that afford mixed-initiative collaboration.

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