Towards Co-Creative Generative Adversarial Networks for Fashion Designers

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Originating from the premise that Generative Adversarial Networks (GANs) enrich creative processes rather than diluting them, we describe an ongoing PhD project that proposes to study GANs in a co-creative context. By asking *How can GANs be applied in co-creation, and in doing so, how can they contribute to fashion design processes?* the project sets out to investigate co-creative GAN applications and further develop them for the specific application area of fashion design. We do so by drawing on the field of mixed-initiative co-creation. Combined with the technical insight into GANs' functioning, we aim to understand how their algorithmic properties translate into interactive interfaces for co-creation and propose new interactions.

Additional Key Words and Phrases: generative adversarial networks, mixed-initiative co-creation, human-AI collaboration

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1 INTRODUCTION

With new technological inventions occurring over time, such as the mechanical loom during the industrial revolution, new possibilities of creating cultural artifacts, such as clothing items, emerge. In the age of industrialization 4.0, we now see how data-driven technologies increasingly find a place in the production cycle of clothing artifacts.[1] With the recent advances in generative machine learning, human-made technology has gotten to a point where tools can *imagine* complex outputs resembling the properties of real objects, such as art [8], faces [17], or clothing outfits [20]. Latent variable models like Generative Adversarial Networks (GANs) learn to generate high-dimensional artifacts given a latent code as input [11]. Via its multiple neural layers, the generator network links the latent codes to output features resembling the training data. The emerging entangled latent space encodes the learned semantics. Due to the latent space's complexity, the connection between latent codes and output features is not traceable for the human eye. While this complex, non-linear structure of encoded semantics impedes the control of generated designs, the emerging design space also makes GANs a novel tool offering new avenues for (co-)creation.

However, with new models for interaction come new challenges [5], primarily caused by the knowledge gap between machine learning models and their potential users. Next to the ongoing research investigating the algorithmic properties of such models [21, 23, 27, 32], a theoretical understanding of how to enfold their potential as creative collaborators in design processes is yet to be developed. Originating from the premise that GANs enrich creative processes rather than diluting them, the ongoing PhD project presented here proposes to study GANs in a co-creative context. By asking *How can GANs be applied in co-creation, and in doing so, how can they contribute to fashion design processes?* the project sets out to investigate co-creative GAN applications and further develop them for the specific application area

[1] https://www.forbes.com/sites/brookerobertsislam/2021/01/27/zara-meets-netflix-the-fashion-house-where-ai-replaces-designers-eliminating-overstock/

of fashion design. We do so by drawing on the field of mixed-initiative co-creation. Combined with the technical insight into GANs' functioning, we aim to understand how its algorithmic properties translate into interactive interfaces for co-creation and propose new interactions.

In the following, we provide an overview of related work to motivate the project, describe the work-in-progress, and conclude with reflections and open questions.

2 BACKGROUND

Caused by the lack of interpretability underlying deep neural networks, designing human-AI interaction remains an open issue in the field of Human-Computer Interaction [29], in which GANs are often applied for providing variation [22]. Utilizing deep neural networks' black-box characteristics as a source of "unpredictability"[2] might add interesting aspects to design processes, focusing on the uncertainty in probabilistic machine learning. Benjamin et al. [2] approach machine learning uncertainty as a design material by proposing a phenomenological analysis of how machine learning models inferred from data affect our relation to the world. How this applies to generative models, often applied for adding randomness to design processes, is yet to be explored. In the specific case of GANs, Hughes et al. [16] find variation as one of the main modes of operation when applied in design tasks, next to beautification. As the first systematic analysis in the area, their survey categorizes what GANs add to design processes in different creative domains. When it comes to interaction, GANs bring new challenges that require specific attention [5].

To understand how GANs can be embedded into co-creation despite functioning as a course of randomness, one needs to turn towards the algorithmic properties behind interactive interfaces. Existing tools like GANLab[3] can to some extend reveal the system mechanics of a black-boxed model with two-dimensional data. However, it becomes difficult to visualize high-dimensional distributions like images, let alone to control the space of possible output images. To navigate the design space of latent variable models with more dimensions, several algorithmic proposals are of relevance to and have been tried out in interactive scenarios. Karras et al. [17] suggest the interpretation of the latent space entanglement by analyzing how generated images respond to interpolations in the latent space aligned with human perception of change (measured as perceptual path length). Applying interpolation in an interactive interface, humans can traverse between artifacts in latent space to explore intermediate versions [10, 22]. Finding hyperplanes that separate the latent vectors corresponding to output faces with and without certain attributes (measured as linear separability) [17] allows for the identification of attribute vectors [24]. These vectors can then be used to manipulate the respective characteristic in semantic editing of e.g. faces [6, 31]. By embedding GANs into an interactive genetic algortihm, Bontrager et al. [3] present a paradigm for controlling the latent space of GANs with latent vector evolution [4]. By selecting images (phenotypes), the user can guide the next generation of artifacts, such as shoes, by indirectly evolving the corresponding latent codes (genotypes). In a similar process, Xin and Arakawa [28] apply conditional GANs to prompt the generation of more specific items, e.g. given the contour of a shoe. Using the disentanglement of secondary latent space [17] instead, Tejeda Ocampo et al. [26] improve the model for the generation of images with more specific constraints due to more control over specific features. These examples originate from investigating algorithmic possibilities and testing them in practice. However, the lack of a deeper understanding for the processes at play in co-creation with GANs as well as in considering designers' needs outlines the knowledge gap between machine learning engineers and designers [16].

Born in the area of games, the research field of mixed-initiative co-creation aims to shed light on how human and computational agents create artifacts together. Spoto and Oleynik [25] and Deterding et al. [7] propose a set of actions

[2]https://www.forbes.com/sites/brookerobertsislam/2020/09/21/why-fashion-needs-more-imagination-when-it-comes-to-using-artificial-intelligence/
[3]https://poloclub.github.io/ganlab/

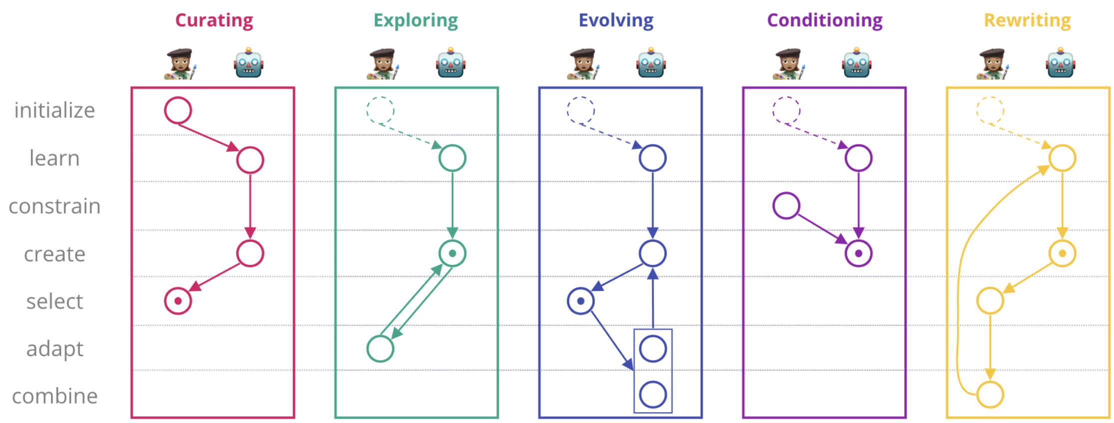

Fig. 1. We present the four primary interaction patterns *Curating*, *Exploring*, *Evolving*, and *Conditioning* we identified as part of our preliminary framework [12]. We suggest a fifth pattern, *Rewriting*, for discussion.

to map the interactions between the agents. Expanded into a framework for analyzing generative AI, Muller et al. [19] suggest to find interaction patterns when designing in generative design spaces. By using theoretical frameworks for understanding mixed-initiate co-creation, we aim to connect the algorithmic development of GANs with their role in the co-creation of artifacts with humans, ultimately allowing us to develop meaningful applications for our use cases in fashion design.

3 WORK-IN-PROGRESS AND REFLECTIONS

The described project is a work-in-progress and follows the goal of creating co-creative GAN applications. As a foundation, we aim to map existing GAN models to analyze their support of and application in (co-)creative scenarios. While reviewing both co-creative and exclusively technical approaches that could potentially be applied in co-creation, we identified patterns in how we currently (co-)create with GANs [12]. To arrive at this classification, we adapted Spoto and Oleynik's [25] and Muller et al.'s [19] framework to a minimal set of actions. Grounded in the algorithmic properties of GANs, the adapted framework distilled four interaction patterns between human and GAN-based computational agents (see Fig. 1).

The identified patterns help us to make sense of how GANs are applied in creative scenarios, specifically in our chosen application domain of fashion design. The fashion label Acne Studios' approach of incorporating GAN generations into their Fall 2020 Menswear Collection falls into the simplest interaction pattern, Curating. The designer(s) chose textures from a GAN's sampled designs without further interacting with the system. The results received the critique of being a "math-crunched amalgam of all previous Acne Studio collections."[4] While this points to the characteristic of a GAN's designs lying within the training data distribution, deducting from the example that GANs have nothing novel to add to creative design processes might be a foregone conclusion. Rather, we suggest to approach GANs' abilities as a design tool, allowing for the exploration the emerging space of *between* cultural artifacts, elevating the phenotype-genotype

[4] https://www.vogue.com/fashion-shows/fall-2020-menswear/acne-studios

mapping to a high-dimensional level for interaction, and maybe even offering new forms of a machine-specific creativity. Utilizing these GAN-specific properties carries the potential of providing novel ways for interactive co-creation.

Differentiated control of GANs applied to fashion design has been achieved through constraining the model with the encoding of a text description [34], sketch drawings [33], or color, texture, and shape inputs through separate losses in the loss function [30]. These approaches can all be understood as Conditioning. The human provides the GAN with a constraint in the beginning without further reacting to the model's creation. Hence, no iterative loop of actors replying to each others' creations is repeated. However, one might postulate that the human could learn the *constraint language* of the GAN by repeating the process. The GAN, however, has neither the option to adapt the design, nor to re-learn. While the former is the case in the Exploring and Evolving pattern, the re-learning during interaction based on human input has been less explored. Bau et al. [1] present the idea of "Rewriting" GANs, suggesting to update GANs' weights based on human's adjustments, which we here map as a possible fifth interaction pattern in Fig. 1. Applied in design processes, patterns could be interpreted as a form of designer modelling [18] remembering the user's preferences through learning. Together with the other iterative patterns of Exploring end Evolving, which have been practically implemented in small-scale experiments of low-resolution artifacts [3, 26, 28] mainly with the purpose of probing the algorithm, the research direction suggests the question: *How do GANs offer new possibilities for personalized design processes?* The pattern of Rewriting expands the collaborative process from designing *with* to designing the GAN *itself* during co-creation.

Underlying is the question of how we define the agents interacting in co-creative GAN applications and their creative agency. While we consider supporting algorithms, such as interactive genetic algorithms, as part of the computational agent in the identified patterns [12], how do we go about generation procedures that include other artificially intelligent components? For example, when a style recognition model steers the generation towards a style identified in an unsupervised manner, would that possibly reveal a machine-specific understanding of style [13]? How generative deep learning is incorporated in co-creative fashion design matters, as clothing stands in an intimate relation to human beings, conveying meaning beyond its material properties using its own language, that the human eye is trained to read [14]. Hence, research is required to investigate how humans make sense of generative models that participate in its design and to reflect on co-creative outcomes of human-GAN interaction.

The goal of the project is to develop GANs for the co-creation between fashion designers and machines. Through user studies, we plan to determine the requirements for conscious and intentional co-creation. We are aware that many datasets available for training generative fashion design models consist of social media and catalog images, highly biased to the presented populations. A crucial part is therefore to enable designers to discuss the data's effect on how stability of a system is reached with regards to design diversity, such as achieving desirable silhouettes while still considering diverse body forms [15].

Fashion designers' expertise can inform the development of applications, that might also become relevant for consumers or other domains. By better understanding how GANs function, and looking at their underlying features, designers may ask how human perception relates to non-human perception and how fashion could look otherwise. Investigating human-machine collaboration in the creative design process contributes to the contemporary debate about creativity and authorship [9]. The proposed research applies a holistic view to the practical issue of applying generative deep learning in the creative field. By bridging the designer's needs and technological capabilities, it aims to develop accountable technology, challenging the status quo of the development of creative AI systems.

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