Neural Design Space Exploration

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We have developed a new tool that makes it possible for people with zero programming experience to intentionally and meaningfully explore the latent space of a GAN. This tool was developed to provide a means for designers to explore the "design space" of their domains. Our work is based on the hypothesis that if a GAN has enough capacity and is trained on enough data from a domain, its learned latent space captures much of the content and structure of the design space of the domain.

While the latent space of a GAN may be capable of capturing a domain's design space, there is still the problem of exploring that space. These spaces contain hundreds or thousands of dimensions which are typically entangled. This means interpolating a sample along any individual dimension will tend to change many of the characteristics of that image. Furthermore, while generating random samples is trivial, intentionally locating a starting point within the latent space based on a target image is not.

Our tool provides technical solutions to these problems, and packages them in a web-based graphical interface that is designed for those with no programming experience. To the best of our knowledge, this makes our work the first example of a *neural* design-space exploration tool. Other types of design space exploration tools exist, such as history-based tools which allow one to visualize and explore the history of designs that they have created, parametric design tools which make it possible to explore a family of designs by tweaking parameterized values, and genetic exploration tools allow one to breed designs in order to create new designs with characteristics of their parents. Our tool combines elements from all three of these, and goes beyond them in that it contains a representation of the full design space.

Our starting point was the StyleGAN2-ada model [4] trained on the Feidegger dataset [5]. We extended the model to achieve the following features related to the exploration of the latent space.

Uploading and Locating Out-of-Sample Images in the Latent Space. It is important for a user to be able to choose the starting point for their design space exploration. For example, a user should be able to upload an example design and find the closest point in the latent space. We employed SGD method described in [1]. Given a starting initialization w, we search for an optimized vector w^* that minimizes the objective loss function that measures the difference between the given image I and the image $G(w)$ generated from w. The optimal w^* is expressed as

$$w^* = \min_w L(w) = \min_w \|f(G(w)) - f(I)\|_2^2 + \lambda_{pix}\|G(w) - I\|_2^2$$

where the loss is calculated as the weighted sum of *perceptual loss* [3] and *pixel-level loss* that is pixel-by-pixel MSE loss between two images. This loss dramatically improved our tool's ability to embed out-of-sample examples in the latent space of the GAN (see in supplementary materials), which made it possible for users to upload their own images and use them as starting points for their design space exploration.

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Image Generation with Text. Another way of finding a starting point for design space exploration is to describe a design and locate that in the latent space. We provided this capability in the form of a text box where users could write a short description of a design. We implemented two methods to locate the design. The first method was to randomly sample images from the latent space, then to pass these along with the text description through a CLIP[6] model to find the image which most closely matched the text. The second method was to fine-tune a DALL-E model [7] on the Feidegger dataset, and then to pass the text descriptions to DALL-E and let it generate designs. Surprisingly, our method produces better results than the DALL-E model, though the DALL-E results were often more unexpected (see in supplementary materials).

Visual Style Mixing. Once starting images have been generated or uploaded, they can be dragged and dropped into the visual style mixing interface. Sliders are provided which allow the user to mix and combine features from each of the designs into a single example. The coarse slider controls shape, and the fine slider controls pattern and color. Style mixing with multiple images is achieved by taking different percentages from each image in the aspect of the coarse and fine features. The output image is shown in the center of the latent-space exploration panel on the right in Figure 1.

Intentional and Intuitive Latent Space Exploration. The latent-space exploration panel allows users to take a starting design and move it along meaningful directions in the latent space. A two-dimensional canvas represents the design space for two attributes in the horizontal and vertical axes. A list of attributes for users to choose is presented in a drop-down menu for each axis. These attributes correspond to semantically-meaningful directions in the latent space. Dragging an image within the canvas is equivalent to interpolating a point in the latent space along the directions selected in the drop-down boxes. Each newly-generated point is shown on the canvas as a history point. Images can be shown or hidden by clicking the point.

Behind the scenes, we used a method described in [2] to identify semantically-meaningful directions using PCA on the latent w space. For example, we found principal components which corresponded to sleeve, pattern, color, and hemline (see in supplementary materials for examples).

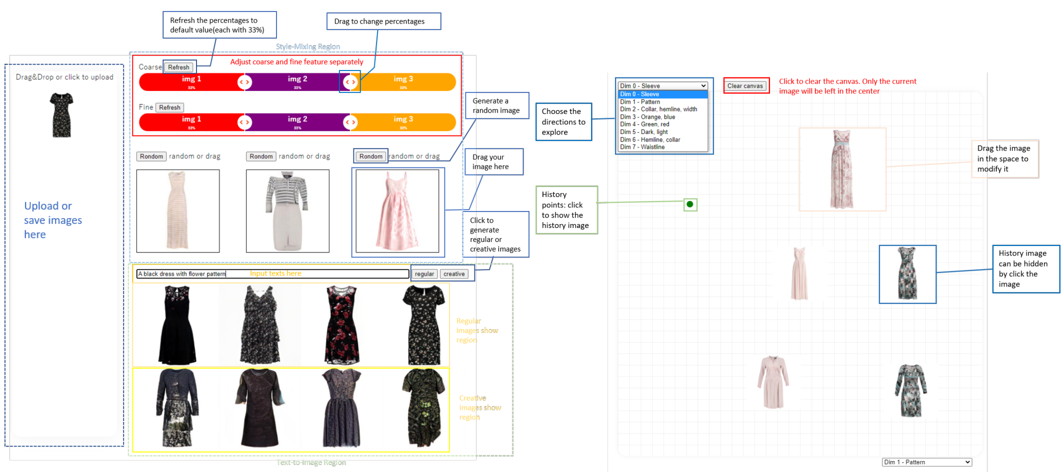

Figure 1: The interface of our neural design space exploration tool. Users can $upload$ images in the workplace on the left or generate random image through $random$ button. Also, they can generate examples via text descriptions using the *text box*. Users can $drag$ these examples to the style-mixing region or save them in the workplace. Users can combine elements three designs using the visual style-mixing panel. The output image is shown in the center of the canvas on the right. The 2D-dimensional canvas represents the design space for two attributes in the horizontal and vertical axes, and these attributes can be changed by using a *drop-down* menu for each axis. $Dragging$ the image within the canvas is equivalent to moving through the design space.

Loading and Exploring Other Networks. Because our work builds on the popular StyleGAN2-ada architecture, weights trained on other datasets can be loaded into the tool and it will provide the same methods for design space exploration in other domains.

Demonstration. A demonstration video can be found in the supplementary materials, and can also be viewed at `https://www.youtube.com/watch?v=dcC7G2zBuL8&t=42s`. A live demonstration can also be found at http://generative.fashion.

Ethical Implications. Because GANs have the capacity to memorize their training data, there is the risk that examples generated using this tool could be very similar or identical to images in the training data. This could lead to a situation where a designer believed they had produced a novel design when in fact they had unknowingly plagiarized another designer's original work. We take this threat seriously and hope to implement a detection system to help prevent this from occurring.

References

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