Art and Machine Learning

AI and Fashion

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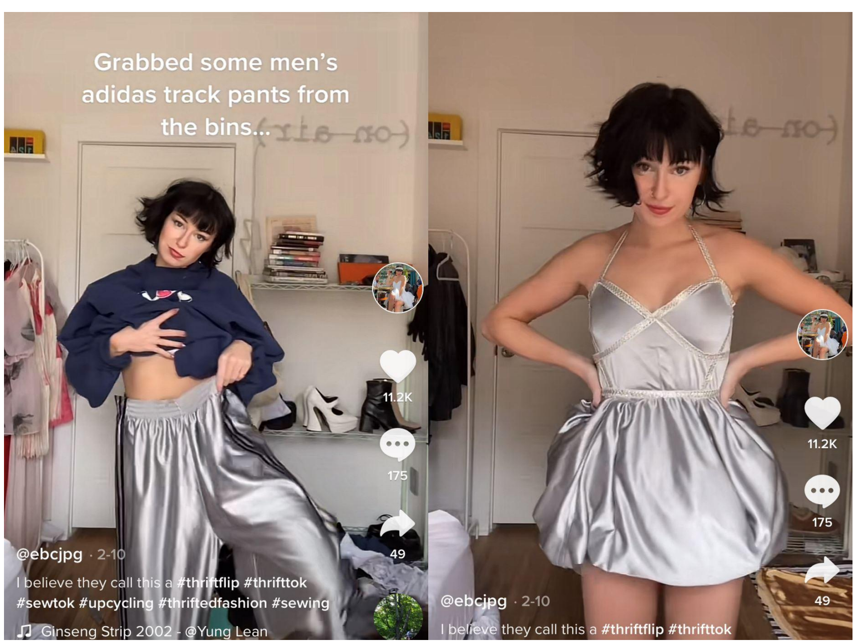
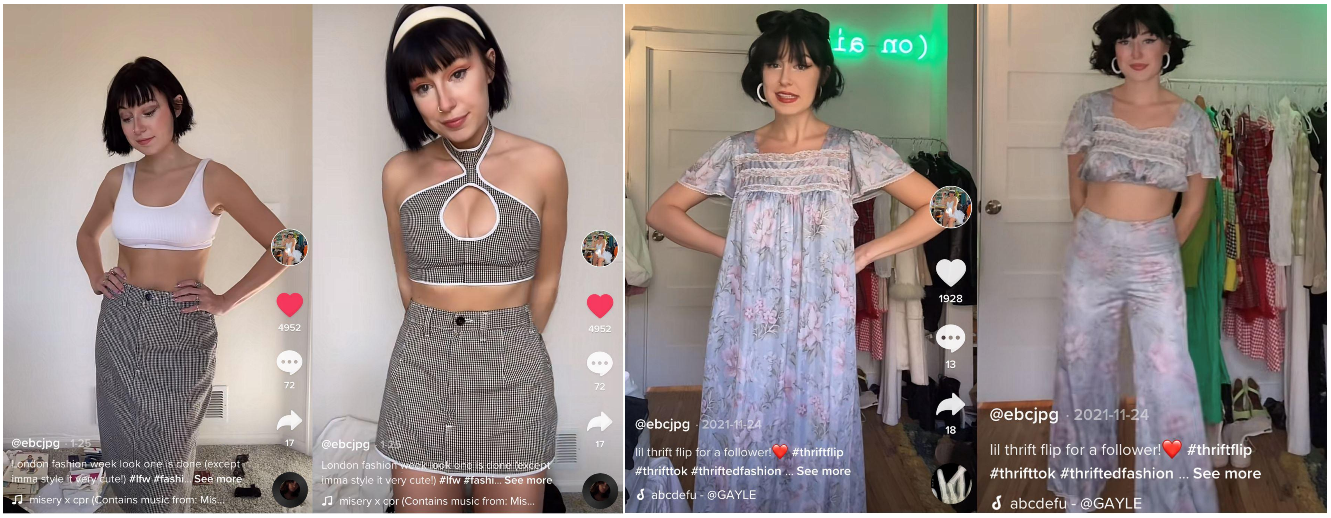
1. Concept

The incorporation of artificial intelligence into the fashion industry is not an new or unexplored venture – in fact, several Instagram influencers, high fashion models, and pop entities are rooted in machine generated technology. Consider, for example, the Japanese computer-generated vocaloid *Hatsune Miku.* Conceived and deployed in 2007, the holographic singer performs at concerts and festivals, using a software voicebank. More recently, in the United States, artificially generated models with millions of followers on social platforms work in conjunction with high fashion brands to depict an exceptionally curated grid of new fashionwear. Consider Miquela (@lilmiquela), a Brazilian model. The influencer has collaborated with brands such as Givenchy, Chanel, and more. In 2018, Miquela debuted at Milan Fashion Week, flaunting the recently launched Prada collection using 3D gifs. Fashion titans such as Balmain have already introduced their first CGI models, such as Shudu and Zhi, who not only have a social media presence, but have also been featured in fashion magazines such as Vogue and Hypebeast.

With our project, we aim not to replace the human element of fashion, nor the human artists, but honor them by continually resurrecting outdated pieces. We took inspiration from young artists on social media who use their platform to showcase ways to repurpose thrifted clothing and raw textiles to fit more contemporary silhouettes and styles. A few of these examples are from Lily Chapman, whose designs are shown below. This first photo shows a pair of silvery track pants that were cut and resewn into a dress.



In these other examples, she takes vintage patterned dresses and skirts and transforms them into two piece sets with modern silhouettes. These were the primary inspirations for our project.



Most current machine learning models trained to generate fashion do not come with an understanding of context, such as the function of handbags or subjective societal rules about where to place accessories. Therefore, they have access to a range of surprising and original silhouettes that have no basis in tradition, and which human designers might not ever conceive. In addition to inspiring designers, this practiced unfamiliarity can accelerate the development of new ideas by extrapolating from decades of original designs. With the rise of fast fashion, we’ve seen corporations constantly mass producing cheap, threadbare knockoffs of classic designer patterns and silhouettes. However, sustainable fashion is also gaining popularity among young people. Many people are learning to sew and craft by following tutorials from artists like Lily and creating original pieces without any professional skills or equipment. However, for people with little fashion knowledge, it can be difficult to understand the most effective use of their material. A tool that allows people to test material against different silhouettes would be extremely useful; people can take photos of their own clothes, knowing what styles best suit their body and photos of materials they want to use to find the best use and avoid creating more textile waste. After examining the role of machine learning in modern fashion, we wanted to explore how Generative Adversarial Models can allow us to reimagine existing clothing to fall in line with constantly changing fashion trends and statements. We dedicated our project to this goal.

2. Technique

In order to generate the images depicting new high fashion trends, we used a generative adversarial model, namely, StyleGAN2. The model comes with several improvements building upon its predecessor, StyleGAN, such as an entirely redesigned adaptive instance normalization to better align style image and content image features, and an advanced training procedure focusing on low to high resolution images.

The new architecture also enhances traditional techniques from style transfer literature, allowing for an entirely new grain of control over output images. By interpolating between various abstracted high level features from input data, a network can be instructed to combine the style contents of an image with simply the gender, facial structure, race, or hair length of another image. In essence, due to state of the art techniques such as weight demodulation and other optimizations, we chose to use this specific network architecture along with its reduced training time to generate our microtrends.

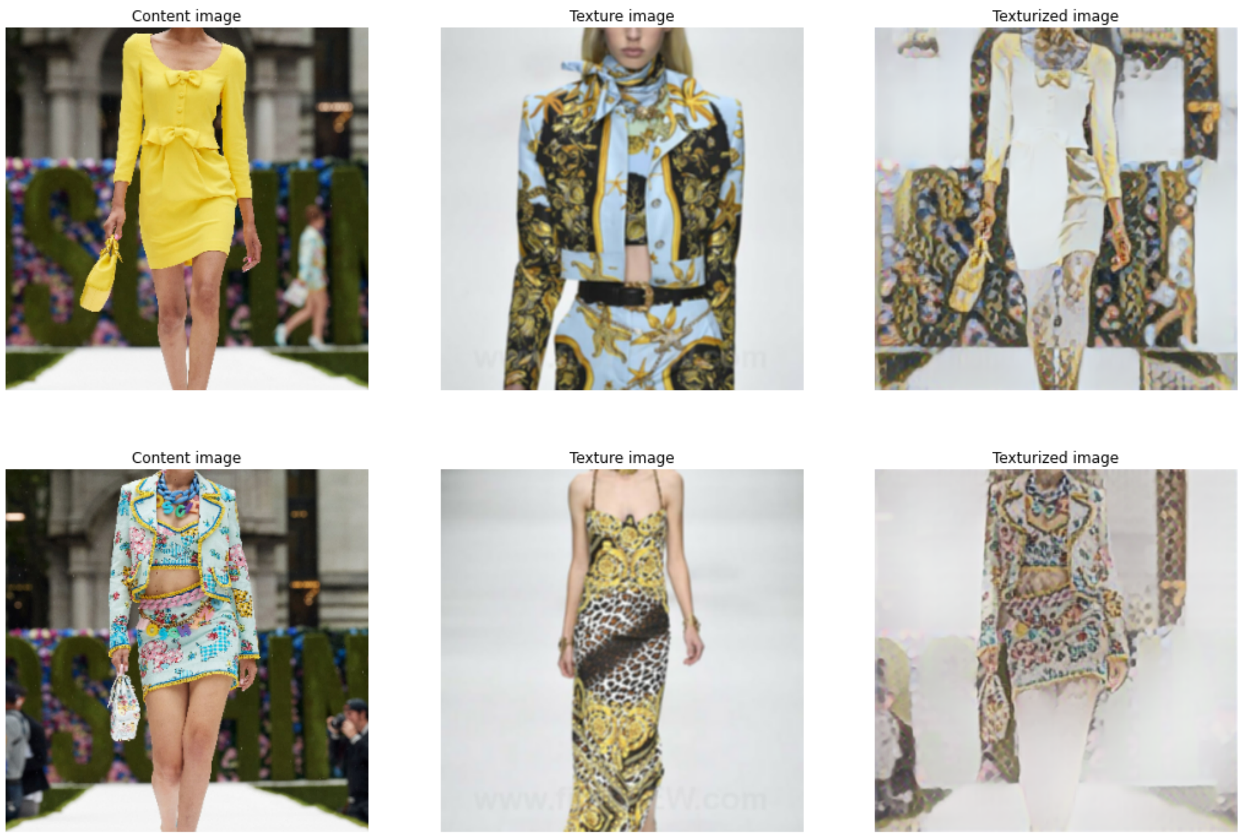
Before deciding upon employing generative adversarial networks, we were considering using a Variational Autoencoder (VAE) to generate the images. The advantage VAEs provide entails compressing an input (an image, in this case) into a much smaller dimensionality latent space, from which the network projects upward. While the technology is promising, the area of Machine Learning with which the technique is entangled involves the reconstruction of input data, while we are more concerned with generating entirely unseen outputs.

3. Process

TextureGAN

Since we wanted to synthesize content silhouettes and style texture patches, we searched for machine learning models that integrated images in this way and came upon TextureGAN, a computer vision and pattern recognition project that uses a GAN to control texture of silhouettes. In this paradigm, users would be able to "drag" texture patches onto sketches and apply these textures to the object.

We had several dependency issues that took us hours to fix, but once we got TextureGAN running, we fed in the original runway photos and texture detail photos to see how the GAN would react and if it would be able to identify the silhouette in the foreground. We received mixed results:



TextureGAN is most often used to fill line drawings of silhouettes with textures from texture images. Therefore, it has trouble recognizing silhouettes from images with many elements, such as models' faces and backgrounds. In an earlier iteration of this project, we aimed to create original silhouettes with AI. However, without involving a GAN to analyze poses of the human body, such as DeepPose, AI struggles to create original line drawings for silhouettes that connect cohesively.

To mitigate this issue, we attempted to use a GAN model trained by Saverio Pulizzi: he used TextureGAN and the fashion MNIST dataset to improve TextureGAN's silhouette detection. However, this didn't improve the issue: outputs were so pixelated that it was impossible to see any distinguishing features of either the original silhouette or the new texture.

We decided to look for other options that could identify silhouettes of garments more effectively: we searched both for models and for data corpuses that might come closer to ready-to-wear high fashion, since that was our input for content and style images.

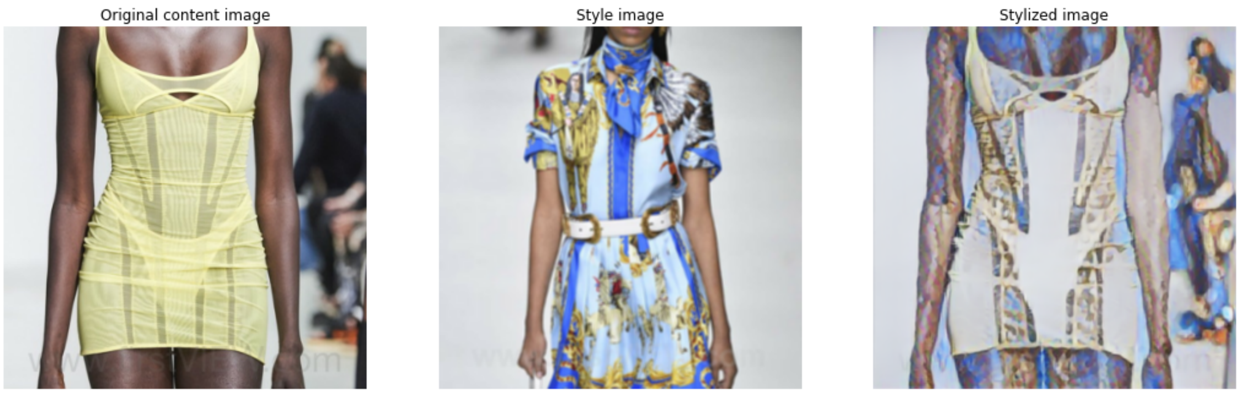
ClothingGAN

Researchers at the Chinese University of Hong Kong compiled the DeepFashion dataset, a compendium of over 800,000 images, and an accompanying set of machine learning models. Many other datasets, such as the fashion MNIST set, are limited to one specific type of image, but the DeepFashion images range from garment-only photos to posed model photos to runway photos. About 20% of these images are available publicly, and the others are available upon request. We requested the dataset and machine learning models, but the researchers didn't get back to us in time, so we were only able to access the limited public-facing dataset.

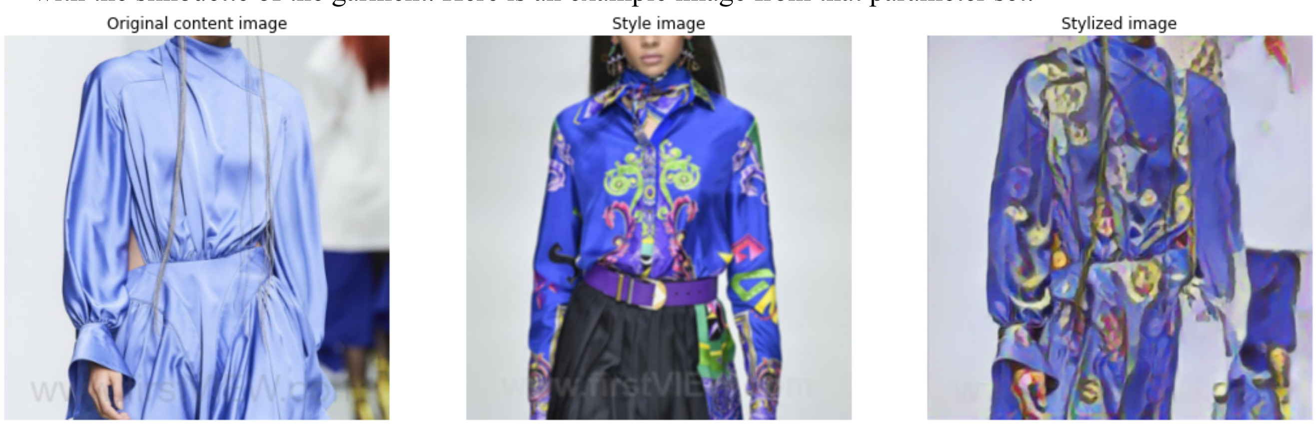
Because of this setback, we weren't able to train the StyleGAN2 model from scratch, since we didn't have access to the volume of data that would be necessary to train a model without overfitting. However, we were able to find a project that uses StyleGAN2 as a foundation: ClothingGAN, originally created at a hackathon, uses StyleGAN2 and the Lookbook dataset to generate and mix clothing images.

We experimented with different parameters while running ClothingGAN to find the optimal parameters for generating clothing that models after the content image's silhouette and the texture image's textile/pattern details. At first, we thought that maximizing the style parameter (for heaviest inclusion of the texture image) would create the most optimal results, but this led to application of the texture over the entire image as a film, including the model's skin and background details, and the silhouette was obscured entirely, as in the image below:

This GAN was trained on white-background images of ready-to-wear garments, so it required a lot of fine tuning of parameters to get the model to distinguish garments from models' faces and backgrounds in runway photos. We reduced the style parameter from 0.9 to 0.7, and saw immediate improvement in selective application of textile characteristics:



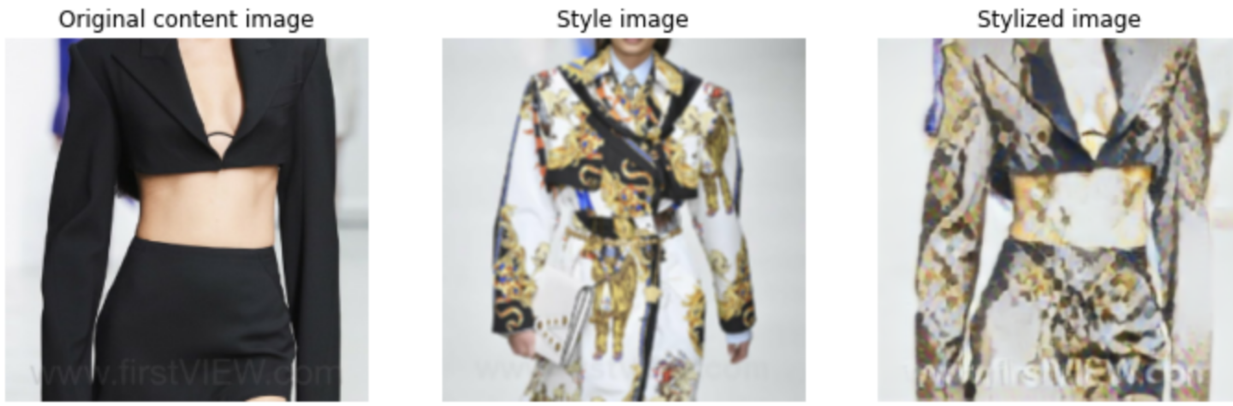
Then we increased the structure parameter from the default of 0.5 to 0.8, to increase identification with the silhouette of the garment. Here is an example image from that parameter set:

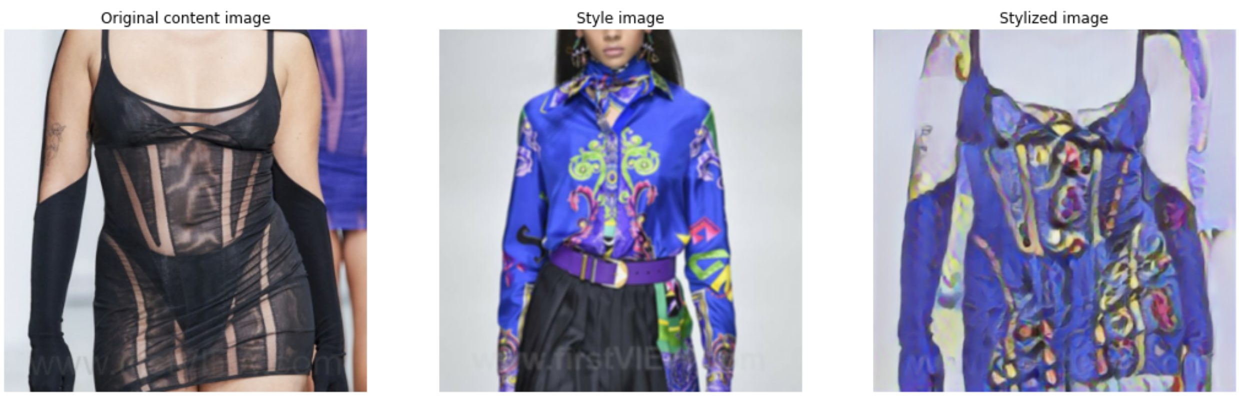


While this shows improvement in recognizing a silhouette and replicating it with the new texture, it still doesn't look like it sees the parts of the content outfit as discrete parts. Rather, it seems to have identified a broad shape and casted the texture of the top onto it. We reduced the structure parameter to 0.6, and got more differentiated results:

The output image does not cast the texture onto the hands of the model, instead focusing only on the garment silhouette. Individual folds and shapes within the main silhouette are preserved, and the details of the style image textile pattern are evident. The stylized image looks like a possible garment. Further results are shown below.

4. Top Final Products Gallery





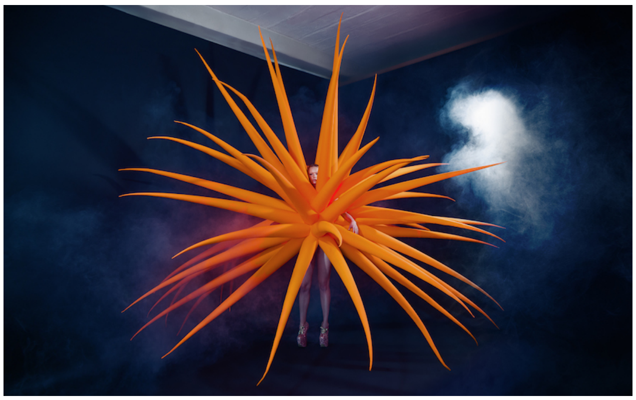
5. Reflections & Future Work

While the results of this project were gratifying and eye-opening, we realize that there are a plethora of avenues in which machine learning can collaborate with the fashion industry to reveal exciting and novel technologies. Throughout this report, we have described how we used the Style-based Generative Adversarial Model to generate fashion trends, but perhaps we could use artificial intelligence to predict the trends and newest fashion statements of the upcoming season. Generally, fashion pieces fall under four categories – Spring/Summer, Autumn/Winter, Resort, and Pre-Fall. Fashion giants generally preview their newly designed pieces at runways before the start of the new season, and the cyclical nature of the timeline provides an interesting dataset and categories for algorithms to classify and sort through.

In the future, we would like to train models to classify new images depicting fashion trends into their respective categories. To advance this idea one step further, we could also use GANs to predict and generate a new fashion piece illustrating the upcoming fashion trends. The cyclical timeline also allows us to easily compare and track the evolution of fashion trends from previous seasons and years, enabling us to extrapolate to future trends.

We need not limit ourselves to analyzing general seasonal trends, but we could also train GANs or VAEs to classify common styles in couture during a time period, through fashion at influential events in high society such as the Met Gala. Such annual events are generally themed, a few examples being “Heavenly Bodies”, “Notes on Camp”, and most recently in 2022, “The Gilded Age”. Training a network to classify the new trends from designers at such events or even generate a new guess for the theme could present as a promising extension of our work.

Another intriguing extension of the Fashion x Machine Learning world, which would require much stronger tools, is AI-generated couture. Thinking about avant-garde and experimental designers, we believe machine learning could be utilized to create vivid and unique designs using nature and science as inspiration. Here are a few pieces by fashion designer Jack Irving, which fall more under the categorization of wearable art than daily clothing:




With the broad ranges of datasets available to train our models, we are interested in what a machine learning algorithm might design using nature as its inspiration. Looking at Jack Irving's designs, the one on the left feels as though inspired by sea urchins. Perhaps the algorithm could take inspiration from other sea creatures, such as this feather starfish (left), or pattern a series of textiles off of this microscope image of a cell (right).


Group Member Backgrounds

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Project Github: https://github.com/malavikakrishnamurthy/ArtandMLP4

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StyleGAN2: https://github.com/NVlabs/stylegan2

FashionGAN: https://github.com/zhusz/ICCV17-fashionGAN

FashionGAN (another implementation): https://github.com/spuliz/fashionGAN

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