DeepWear: a Case Study of Collaborative Design between Human and Artificial Intelligence

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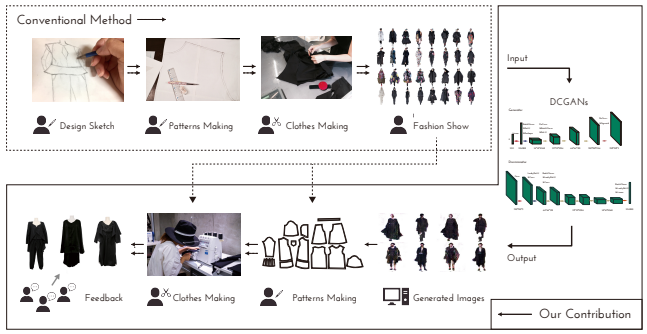

Figure 1: Our system's workflow. Conventional fashion design is a feedback loop. First, designers make their clothes design. Next, patterners draw patterns from the design and designers instrucion. The We use DCGANs to make new feedback loop. Fashion design process In this process, making design inspiration easier for designers.

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Abstract
Deep neural networks (DNNs) applications are now increasingly pervasive and powerful. However, fashion designers are lagging behind in leveraging this increasingly common technology. DNNs are not yet a standard part of fashion de sign practice, either clothes patterns or prototyping tools. In this paper, we present DeepWear, a method using deep convolutional generative adversarial networks for clothes design. The DNNs learn the feature of specific brand clothes and generate images then patterns instructed from the images are made, and an author creates clothes based on that. We evaluated this system by evaluating the credibility of the actual sold clothes on market with our clothes. As the result, we found it is possible to make clothes look like actual products from the generated images. Our findings have implications for collaborative design between machine and human intelligence.

Author Keywords
Fashion; Creativity support; DCGANs.

Introduction
Recent advances in computational fabrication have afforded the opportunity to use automated tools and machines to support fashion design. However, obtaining inspiration of fashion design is still a difficult task. To address this challenge, there are projects to improve the process by incorpo-

rating DNNs into fashion design, such as Project Muze[1] or Amazon's AI [14]. Project Muze use DNNs to learn the trend and design clothes. Amazon's DNNs are GANs based architecture. To internalize properties of a particular style simply by looking at many examples and apply that style to existing clothing. However, there are articles [22, 25] which doubt as to whether the styles created by Project Muze are actually that people can wear. Also, since Amazon's AI is still in the development stage, these projects are not still practical.

In this work, we present DeepWear, practical designing clothes system use DCGANs [23] to generate images and designers make clothes by receiving instruction from those images. State-of-the-art deep learning techniques are first applied to the workflow of designing clothes. The system takes specific brand [2] clothes images as the input, learns the feature of inputs, generates images that looks close to the clothes, then patterns instructed from the images are made, and an author creates clothes based on that.

In the evaluation, we conduct a content analysis about the theme related to our system practicality by comparing the actually sold clothes with our clothes and other brand clothes by questioning which are the actually sold the specific brand clothes. The results show that our system is possible to make clothes look like actual products from the generated images. This paper shows the implications for collaborative design between machine and human intelligence.

Related Works

Image Generation

Recently, the deep generation model has attracted a lot of attention and the ability to learn large (unlabeled) data potential and vitality [3, 24]. In [7], the deep belief net (DBN) using a contrast divergence algorithm was initially proposed to efficiently training. denoising autoencoder (DAE) learns data distribution with supervised learning method [3]. Both DBN and DAE learn the low dimensional representation (encoding) of each data instance and generate from the decode network. In recent years, Variational AutoEncoder (VAE) combine deep learning and statistical inference for represent data instances in a latent [13] hidden space while utilizing a deep neural network for nonlinear mapping is used. All of these generation models are trained by maximizing the possibility of training data i.e. generative adversarial networks (GANs) [6] are generative model which are minimax game between generator model and discriminator model. This framework avoids the difficulty of maximum likelihood learning and has remarkable success in natural image generation [4].

GANs show impressive results in image generation [4], image transfer [11, 30], super resolution [15] and many other generation tasks. DCGANs utilize deep convolutional networks architecture and batch normalization [10] to extract the feature [23], and show significantly great output. Therefore, in this study, we used DCGANs architecture for image generation network.

Machine Intelligence Creativity Support

In other than fashion design, there are researches to support human creative activities by incorporating machine intelligence. AutoDraw is a new kind of drawing tool that combines machine learning and drawing of an artist so that anyone can create something visual quickly [9]. User experience designers integrate machine learning services in new apps, devices, and systems [5, 28]. Many studies have been issued for the purpose of supporting the creation of cartoons and animation. There are systems that inputs black-and-white line drawing manga images and automatically outputs colored images [29]. In order to support

character design, there is research to automatically generate facial images using GANs [12]. The method to identify structural lines from pattern-rich cartoons without being conscious of patterns is developed [18]. Extracting structural lines from pattern-rich manga is an important step for transferring legacy manga to the digital domain.

Machine Intelligence & Fashion Design
There are several works trying to support or recommend everyday life fashion design [26]. Especially, there are many recommendation[19, 20] or classification systems [21, 27]. Heterogeneous graphs to link fashion items, make up stylish costumes, and link items to their attributes are used [16]. In [8], a tensor decomposition approach is proposed to recommend a set of fashion items. Rather than learning item features based on sets, use discrete item attributes or low-level image features. In [17], implemented a representation learning framework for fashion items that includes latent styles in which learned expressions are shared by items in the style set.

Research AI fashion design. Project Muze [1] is based on Google's open source TensorFlow[1]. It is developed as a predictive design engine. It consists of two parts: neural networks and a set of aesthetic parameters. The neural network learn the color, texture and style preferences of over 600 fashion experts. Over time, it learned to connect those preferences to other people with similar interests. Then a set of aesthetic parameters from the Google Fashion Trends Report and Zalando's[2] deep knowledge of fashion trends is used to refine the designs and make sure they're fashion forward. However, there are articles doubt whether the styles created by Project Muze are actually the structures that people actually can wear [22, 25]. Amazon's Project use GANs based DNNs architecture [14] internalize properties of a particular style simply by looking at many examples and apply that style to existing clothing. Amazon's AI is still in the development stage, and these projects are not yet practical.

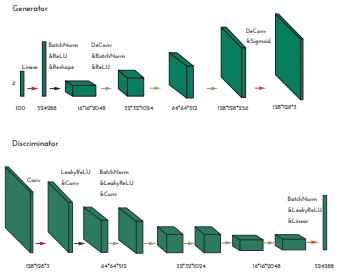

Figure 2: Our Networks

In summary, our approach is distinct from the above in that we aim to make practically usable clothes from a specific brand clothes dataset. Our approach captures fashion semantics on the style space, which can be effectively utilized by fashion design systems. We asked patterners to write a pattern based on the generated image, and investigated whether we could actually make clothes. Finally, we implemented clothes based on that pattern and user-studied the quality.

Deep Convolutional Generative Adversarial Networks

Deep Convolutional Generative Adversarial Networks (DCGANs) is a neural networks that has been popular in recent years. This lets the network learn to generate data with the same internal structure as other data (Figure 2). One of the most common applications is image generation. The Generative adversarial network consists of a generator network *G* and a discriminator network *D*. Given training data *x*, *G* will take input from random noise *z* and try to generate data with distribution similar to *x*. The discriminator network *D* receives inputs from both *x* and the generated from *G* and estimate the probability that the sample came from the training data, not *G*. *G* and *D* are trained at the same time: Adjust the parameters of *D* to maximize the probability of assigning the correct label to both the training example and the *G* sample, and adjust the parameters of *G* to minimize $\log(1-D(G(z))$. In other words, *D* and *G* play the following two player min-max game with value function $V(G,D)$ (1).

[1] https://github.com/tensorflow/tensorflow (last accessed January 9, 2018)

[2] https://www.zalando.co.uk (last accessed January 9, 2018)

$$\min_G \max_D V(D,G) = E_{x\sim p_{data}(x)}\big[\log D(x)\big] + E_{z\sim p_z(z)}\big[\log(1-D(G(z)))\big] \quad (1)$$

Figure 3: Making clothes from patterns.

Figure 4: Our system's output clothes.

data collection

We collected images of a specific brand announced between 2014 and 2017. We used web scraping Python code to create the training dataset. Scraping consists of three steps. In the first step, follow the link from the top page of the target website. Second, we list all HTML pages with the URL structure as directory structures. Then, we acquire all the image URLs specified by *src* of the *img* tag in the HTML pages detected in the second step. In the third step, we downloaded all image URLs. In order to prevent overloading the server, we restricted the request to 10 times / 1 s. For pages that restricted crawler behavior by robots.txt, we followed that restriction. As the result, over 1.1K images were collected. Several steps were performed to learn the feature of the images. We paint the background white so that only people and clothes are cut out, and processed it into full color image of 128 px x 128 px (resized dataset is here.[3] (last accessed January 9, 2018)).

Training

We implemented our network with Chainer[4], a deep learning framework. We followed implementation and training procedure recent work by Radford et al. [23]. Our network architecture is shown in Figure 2, where training was done with a batch size of 7, using Adam with hyperparameters (α=0.0002, $\beta_1 = 0.5$, $\beta_2 = 0.999$, $\epsilon = 1e-08$), and run on an NVIDIA Titan X GPU for 1000 epochs. We stopped running around 43000 iteration (about 270 peoch), because the loss has become quite small and generated images looks good. At the 43,000 iteration, G loss is 16.1374, D loss is 1.39158.

[3] https://drive.google.com/open?id=0BywMLxsmMEnROGNKZzAtVkR3aFE

[4] https://github.com/chainer/chainer https://drive.google.com/open?id=0BywMLxsmMEnROGNKZzAtVkR3aFE (last accessed January 9, 2018)

Clothing implementation

Draw Patterns

Seven participants(6 females and 1 male) aged between 21 and 23 years partcipated. They experienced fashion design patterners and had clothing experience of 1 year and a half to 5 years (Patterners are people who draw patterns of clothes based on instructions from designers). We ask them to draw patterns based on images generated by DCGANs. This work were done under the presence of an author or by online calls. We set time limit 70 minutes for all subjects. The pattern created for the first was the image in Figure 5 A, the second pattern was asked to draw the pattern based on the image selected by each subject (shown in Figure 5 B). Subjects were asked to use writing tools such as rulers and pencils are usually used when drawing patterns. Actually, they made a pattern of size within the required time, not full size sufficient to make clothes. The patterns that the patterner drew based on the image we specified are the Figure 5 A, and drew based on the images selected by each are the Figure 5 B. The numbers (1) - (7) are the numbers of the subjects. Based on the generated image, the patterners drew patterns with each idea. In A, 4 out of 7 of the subjects drew a pattern of a combination of a one-piece dress and outer. Two subjects drew a one-piece dress pattern. One person drew a pattern of tops, skirts, and outer combinations. Six subjects drew one-piece dress patterns.

Make Clothes from the Patterns

Based on the pattern that the patterner handwritten, tracing with Illustrator, converting it to data, making it the size of the

full size that can be worn as clothes. Then, using two kinds of black cloth, an author made three kinds of clothes from drawn pattern by two subjects. The working time was about 50 hours.

We found that the silhouette considerably. Figure 4 shows images of clothes. A (1) and B (1) are produced based on the pattern made by subject 1 pattern and B (2) are based on subject 2 pattern.

A (1), B (1) are clothes made using black cotton sheeting, B (2) has a shiny feeling and is made from a heavy black cloth. Sheeting is a cloth generally used for prototypes, the density of weaving is low, breathable fabric and thin. B (2) was made with a heavy, shiny, soft-touching and thick cloth. The concept of the brand used as data set of the generated image is to break the stereotype of gender by incorporating the style of male clothes into women's clothes. One of its characteristics is that clothes are oversize. Looking at the output clothes, the B (2) made of a heavy black cloth dropped down the silhouette of the entire clothing than the A (1) and A (2) made of the sheeting. Therefore, we think that making clothes with a heavy black cloth was able to capture the characteristics of the original data brand.

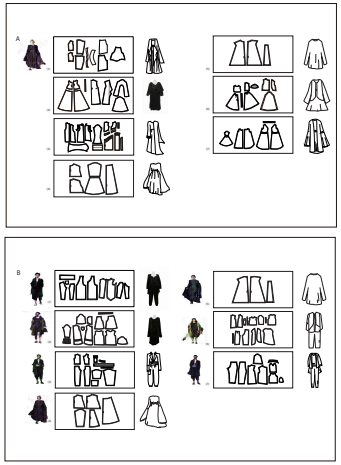

Figure 5: Patterns made from the patterners. A patterns are drawn from same image by each patterners, B patterns are drawn from what patterners selected.

Qualification & User Reaction

We conducted an experiment to evaluate whether the image generated from DNNs can be instruction sources for creating a new clothes. The experiment is evaluating the quality of the actually sold clothes on market with our clothes and the other brand clothes.

Participants

Thirty two people who didn't experience clothes design (14 females, 18 males) aged between 19 and 61 years (M = 24.3, SD = 8.96) answered this questionnaire.

				Ave
Other	80 (1)	78 (5)	97 (7)	85
DeepWear	121 (3)	87 (6)	107 (8)	105(+23.5%)
Source brand	131 (2)	120 (4)	115 (9)	122(+43.5%)

Table 1: The result of the questionnaire that to distinguish the source brand clothes.

Experimental Design

We prepared images of the source brand and output of our method and clothes images of other brands[5][6][7], respectively three. To the subjects, six clothes of the source brand were first exemplified. After that, we asked clothing images one by one in random order and evaluated whether or not the displayed image can be seen closer to the product of the source brand in 7 stages of 1 (looks different) to 7 (looks learning source brand).

Result & Discussion

An weighted averages of these results are shown in the Table 1. For the costumes designed based on our system, they are understood that the subjects were more impressed by the learning source brand and ours than the other brand costumes. In addition, we have shown that our output is close enough to the learning source brand, as the output costumes are significantly closer to the learning source brand than other brand costumes. Looking at the answers of the subjects, the clothes that were judged to be most similar to the clothes of the original brand were the output of our system (Table 1: (3)) and the clothes of the actual learning source brand.

[5] https://page.auctions.yahoo.co.jp/jp/auction/v499221070

[6] https://page.auctions.yahoo.co.jp/jp/auction/260446858

[7] https://page.auctions.yahoo.co.jp/jp/auction/m218550387 (last accessed January 9, 2018)

Figure 6: Wearing DeepWear.

The concept of the brand is to emphasize genderless design, however for image 6, we think that the chest race was emphasized as a feminine design, so it doesn't look like the brand. It is difficult for a patterner to judge detailed details from the generated image, and we thought that the difference has come out by the intention of the patterner entering the design. From the above, since the silhouette of the clothing is greatly different depending on the cloth used as the material, we consider important to choose which cloth to use in order to make clothes similar to genuine brand clothes. In addition, many of the clothing of the learning source brand are black in color and simple design, so texture of the cloth is more emphasized. Also, garments made entirely with large silhouettes tended to resemble real ones.

Patterners Feedback to Experiment
We took a questionnaire on how the patterner sees the answer to this experiment.

Some of a kind are quite simple clothes, but if they are not similar, looking at the whole and putting effort into detail such as frills are attached to the front neck.

(Patterner 1: Male, 21, design experience 1 and half years)

I think that the judgment criteria of similarity or dissimilarity are mainly the length and the whole image. I thought that it was judged by those with a center of gravity on the upper body were not judged to be similar, the lower body had a center of gravity, and those with a long sense of resemblance were similar. Also, I think that it was difficult to judge that many cases of the brand have the similarities like oversize, straight line, and big silhouette image because the waistline of other companies' brand products is narrow.

(Patterner 2: Female, 22, design experience 3 years)

I think that the feature of the specific brand's design is silhouette that is comfortable between the body and clothes, so I think that such a silhouette design was chosen as the brand. I felt that the thing judged not to be similar was judged that detail or material are not like the brand. I thought that the brand does not have much design of material like organza decorated with neck tuck.

(Patterner 3: Female, 22, design experience 5 years)

Conclusion

DNNs are now a fairly established technology, and fashion designers have begun to integrate DNNs application into the things that they design. This paper presents a system conducted with application DCGANs to design clothes in practice. When asked the patterner to write a pattern based on the generated image, a pattern which can actually make clothes was created after obtaining a good response from the patterner to the work. Finally, we implemented clothes based on that pattern and we conducted a user study on that quality, and found that the clothes made by DeepWear are high quality clothes. Our findings show that our system enable collaborative design between machine and human intelligence. We expand on these findings to present a series of challenges for DNNs and fashion design research.

Video link (https://youtu.be/pVlLwvRVdb8)

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