Master's Thesis in Graduate School of
Library, Information and Media Studies

Creative Clothes Design Process by Collaboration between Human and Machine Intelligence

March 2019

201721658

Natsumi Kato

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Graduate School of Library, Information and Media Studies

University of Tsukuba

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Student No.: 201721658
Name: Natsumi Kato

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 design 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 , we found it is possible to make clothes look like actual products from the generated images. Also we propose a method of generation of clothing images for pattern makers using Progressive Growing of GANs (P-GANs) and conduct a user study to investigate whether the different image quality factors such as epoch and resolution affect the participants' confidence score. We discuss the s and possible applications of the developed method. Our findings have implications for collaborative design between machine and human intelligence.

Academic Advisors: Principal: Yoichi OCHIAI
Secondary: Tetsuji SATOH

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Chapter 1

Introduction

This thesis is written in two parts which describe two different studies on fashion by machine learning. First theme is written about research of generating fashion design by machine learning instead of designer and collaboration between human and machine intelligence in the process of making clothing. Second theme is written about how pattern-making craftsmen called Patterners can make patterns with accuracy of generated images by machine learning. In this two researchs, for a long time, I have studied the process of making new clothing by newly introducing machine intelligence into the production of clothes done by human hands.

Fashion production has been produced by human hands from design drawings until actual clothes are completed. In the industry such as clothing and decoration, we produce products based on sensibilities and technologies of prominent artists. These sensibilities and technology are based on years of experience and feeling of the writer himself, there are problems that protect the tradition of sensitivity and technology, and there is a problem that design is not easy to inherit. Moreover, Designers are loved and known by their specific styles and features. However, it is difficult to maintain the level of creativity in designing while maintaining their own styles. Especially in fashion design, the newest of clothes are announced globally every season in the form of fashion shows. Maintaining the characteristics of his own design in intense production schedule, while making novel work is a big challenge for designers. Therefore, I thought a new fashion production by using machine learning to make it possible to inherit traditional design and obtain design inspiration.

Machine learning with remarkable development in the field of information science to the field of traditional art that is difficult to inherit will revolutionize the production process of clothing and decoration fields. Recently, in the field of information science Machine learning with remarkable development has been extensively studied as a technology to replace a part of human intellectual activities. In this first research project, it is aimed to change the production process of clothing and decoration using learning technology and to revolutionize clothes culture. In the past, The creation depended on the writer, but realizing the idea source and production process with human and mechanical intelligence in cooperation work, substitute some or all steps of the production process that has been done manually until now. Moreover, when fashion production is carried out using this research method, when a patterner uses a generated image by machine learning as a fashion design picture by a designer and a patterner produces a paper pattern. This research method will be new making fashion process for new era.

On the other hand, in the second study, I thought that when a patterner creates a pattern in first study, high quality is not necessary for pattern making. The patterner always reflects its design faithfully in patterns by the designer rough sketch. However, in the first research, when patterns made patterns from a generated image instead of a designer's rough sketch. The patterners have a certain degree of freedom in the pattern making process. Also, even if we designed clothes from the same generated image, each pattern made varies slightly from different patterners. In the field of machine learning, research is carried out with emphasis on improvement of accuracy, however it was thought that it is not always necessary to generate high quality images in clothing production. It is important to understand to what extent the accuracy of the generated image is necessary to make it possible to make clothes by fashion design using patterned images instead of the designer's rough sketch. If so, you can create clothes mainly by patterners. In other words, even if there is no designer, patterners will be able to produce clothes as a designer and a patterner.
Recently, in the field of machine learning, researches on image generation of clothes and designs using deep learning are actively conducted. Most of the researches have been made from a consumer's viewpoint, such as images discrimination of clothes using machine learning[1, 2] trend predictions[3], coordination articles[4]. On the other hand, few researches are done on the production process all the way from clipping to actual production of clothes from generated image. Next, a pattern maker draws a pattern with precise measurements of the clothing based on the design sketch. Finally, sewing craftsmen make the clothes based on that pattern. Machine learning researchers are devoting much effort to generate high resolution image in hope of bringing it closer to the actual sketch. However, such tasks consume large amount of time and computation resources. In addition, as quoted above, it is possible to produce clothes even with the low resolution image generated by GANs as a design sketch. In the process, the impact of resolution of the generated image by machine learning on actual clothes production is questioned. Therefore, we conduct experiments on people who actually participate in clothing production. Based on the s,we clarify the degree of quality a pattern maker needs to draw an accurate patterns from the generated image. As a result, image resolution and epoch number are not the main factors in pattern making, but the pattern makers who are experienced and knowledgeable in the source brand designs in pattern making using the generated images.

1.1 Current Process of Making Clothes

The process of making clothes can be roughly divided into four processes. As shown in Figure A, the creation process of the creation thing is roughly divided into (1) the idea of the work and the simple reproduction, (2) the preparation of the specification of the expert, (3) the production of the work, (4) Evaluation, and evaluation. Details of each step will be described in detail below. The idea and simple reproduction of the work A writer gives

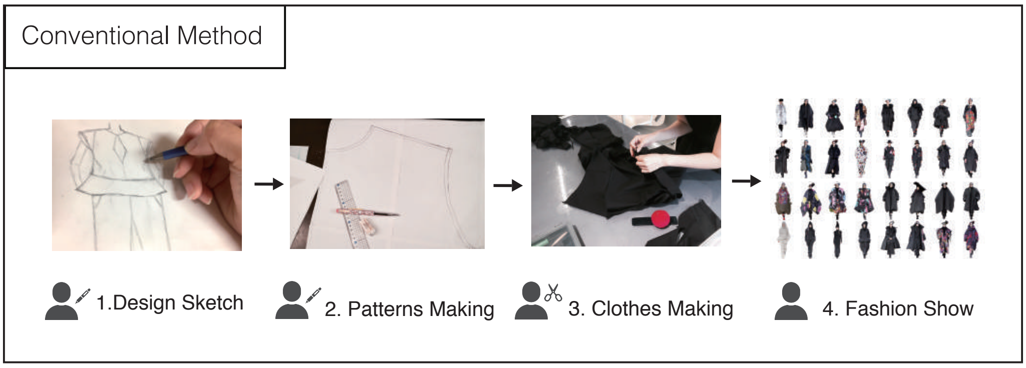


Figure 1.1: Conventional clothes making process is divided in to four process. These process is done by only human hands.

out the concept and idea of the work, reproduces it with abstract ideas and rough plots and sentences of various expressions, three-dimensional model. Therefore, it is possible to use image generation of machine learning as an idea source of the work. (2) Creating Specifications by Experts Specialists prepare specifications with the optimal professional method for rough drawing (rough sketch) produced by artists. We believe that substitution by machine learning will be possible in the future 3) Production creation It is the stage of implementing the production based on the designed specifications designed. In order to reduce the difference between the artist's imaged product and the idea, tell the modification point and the idea again with verbal or sentences to the producer of (3) and the specification designer of (2). 4) Presentation and Evaluation of Productions It is the stage of making feedback on evaluation and verification after announcing productions. (1) to (4) are carried out many times to connect the knowledge obtained at this stage to the next work. Among these four stages, by substituting machine learning for the rough drawing design creation in the process of (1), human beings and machine intelligence can perform collaborative work, and the creation of a process of designing a new clothing field This is the purpose of this research.

1.2 Our Method of Making Clothes Process

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 incorporating DNNs into fashion design, Amazon's AI[5]. 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. Since Amazon's

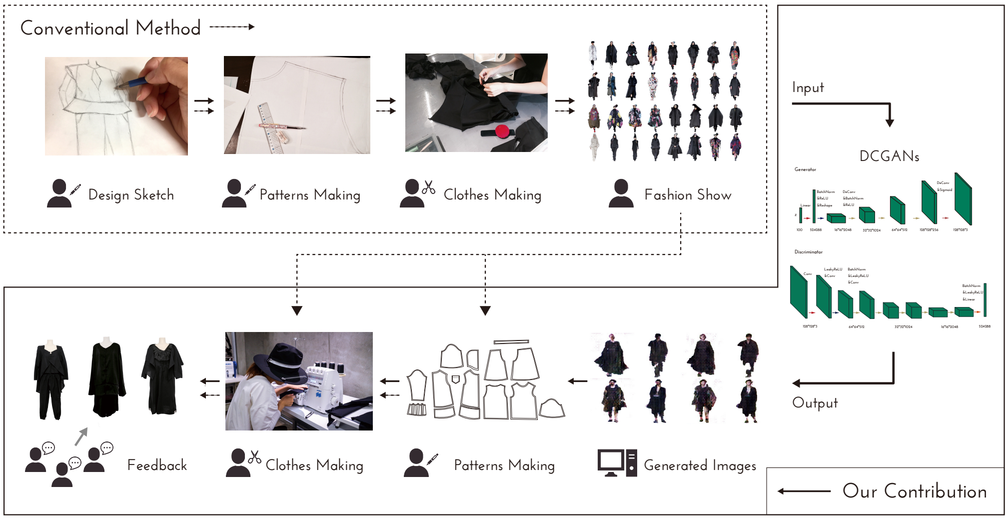


Figure 1.2: Our system's workflow. Conventional fashion design is a feedback loop. First, designers make their clothes design. Next, patterners draw patterns from the design and designers instrucion. The We use DCGANs to make new feedback loop. Fashion design process In this process, making design inspiration easier for designers.

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[6] 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[7]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 s show that our system is possible to make clothes look like actual products from the generated images. This paper shows making fashion process for collaborative design between machine and human intelligence.
There are a number of researches that aimed at creating new designs through image generation, but few directed towards the process of actually producing the clothes. In the process of actual clothing production, often there is a pattern maker besides the main designer in sketching a pattern according to design picture. Traditional fashion production can be briefly described in the following steps. First a design is visualized by the fashion designer in the form of a rough sketch. Next, a pattern maker draws a pattern with precise measurements of the clothing based on the design sketch. Finally, sewing craftsmen make the clothes based on that pattern. Therefore, we conduct experiments on people who actually participate in clothing production. Based on that, we clarify the degree of quality a pattern maker needs to draw an accurate patterns from the generated image. As image resolution and epoch number are not the main factors in pattern making, but the pattern makers who are experienced and knowledgeable in the source brand designs in pattern making using the generated images.

Chapter 2

Related Work

First, image generation by machine learning. Second, machine intelligence for creativity which is recent making products between human and machine intelligence. Third, Machine Intelligence and Fashion Design which which is more focused about fashion creativity between human and machine intelligence.

2.1 Image Generation

Recently, the deep generation model has attracted a lot of attention and the ability to learn large (unlabeled) data brings potential and vitality[8, 9]. In[10], 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[11]. 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) that combine deep learning and statistical inference for represent data instances in a latent[12]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)[11]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[13]. GANs show impressive s in image generation[13], image transfer[14, 15, 15, 16]super resolution[17]and many other generation tasks. DCGANs utilize Deep Convolutional Networks architecture and Batch normalization[18]to extract the feature[6], and show significantly great output. Therefore, in this study, we used DCGANs architecture for image generation network.

2.2 Machine Intelligence for 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[19]. User experience designers integrate machine learning services in new apps, devices, and systems[20, 21].

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[22, 23, 24]. In order to support character design, there is research to automatically generate facial images using GANs[25]. The method to identify structural lines from pattern-rich cartoons without being conscious of patterns is developed[26]. Extracting structural lines from pattern-rich manga is an important step for transferring legacy manga to the digital domain. The method is useful to digitalize manga.

2.3 Machine Intelligence and Fashion Design

There are several works trying to support or recommend everyday life fashion design[27]. Especially, there are many recommendation[28, 29, 30]or classification systems[31, 32, 33, 34]. Heterogeneous graphs to link fashion items, make up stylish costumes, and link items to their attributes are used[35]. In[36], 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[37], implemented a representation learning framework for fashion items that includes latent styles in which learned expressions are shared by items in the style set. Google's open source TensorFlow1 is used as AI's fashion design. 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 learn to connect preferences to other people with similar interests. Then a set of aesthetic parameters from the Google Fashion Trends Report and Zalando's deep knowledge of fashion trends is used to refine the designs and make sure they're fashion forward. Amazon's Project uses GANs based DNNs architecture[5] 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.
In summary, our approach is focusing on making clothes process instead of designer's rough sketch and clothes actually wearable by machine learning design.

Chapter 3

Implementation of Generating Image for Fashion Design

3.1 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 3.1). 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 $V(G, D)$ (3.1).

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

3.2 Data Collection

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 per second. For pages that restricted crawler behavior by robots.txt, we followed that restriction. As the , 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.

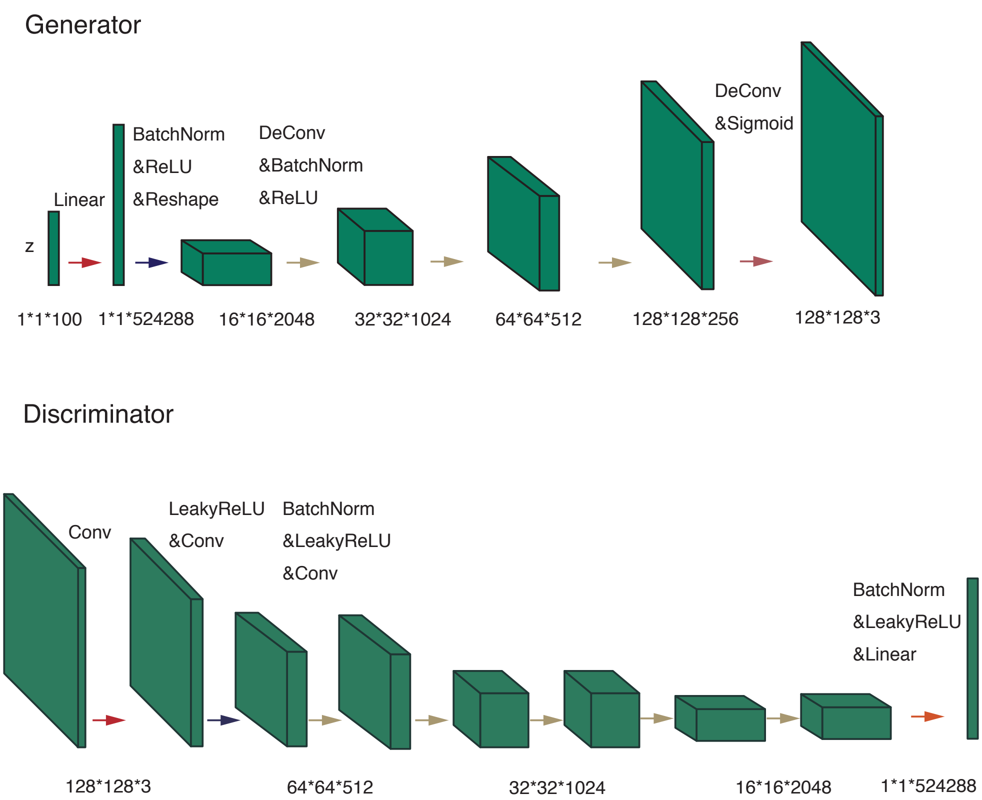


Figure 3.1: Our Networks

Figure 3.2: Collected source data

Figure 3.3: Resized source data (128px)

3.3 Training

Training We implemented our network with Chainer4 , a deep learning framework. We followed implementation and training procedure recent work by Radford et al.[6]. Our network architecture is shown in Figure 2, where training was done with a batch size of 7, using Adam with hyperparameters (a=0.0002, b1=0.5, b2=0.999, e=1e-08), and run on an NVIDIA Titan X GPU for 1000 epochs. We stopped running around 43000 iteration (about 270 epoch), 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. The output images are shown in Figure3.4

3.4 Study Design

We investigated what kind of clothes images can be made from this generated images by participants who don't have clothing experience. The reason is investigating how much fashion design image by machine learning can be represented for general people. We showed 10 generated images Figure3.5 around 43000 iteration and them 45 clothing patterns (pattern images are retrieve from[38, 39, 40, 41]). After that, we asked them to select the clothing patterns which they presume corresponds to the generated images. The pattern list consists of tops (jacket, blouse, best) and bottoms (pant, skirt), and participants chose combination of them one or more. In the case of one-piece dress, they didn't need to choose two or more patterns. In the case of layering cloth, they were able to choose as many as they like. Then, we asked them to write free description about the thought when they selected clothes from

Figure 3.4: Generated images)

the generated image. To conduct the survey online and to analyze the s, we collated answers and analyzed the answers provided by multiple choice questions using simple statistics.

3.5 Participants

Seventeen people who didn't experience clothes design (6 females, 11 males) aged between 18 and 61 years (M = 24.8, SD = 10.2) answered this questionnaire.

3.6 Results

As the of the experiment, 56 % of subjects said that they were "difficult" for this experiment, and many subjects responded without understanding pattern completely. In addition, half of the subjects who answered that they were difficult answered that the classification of the pattern type was not clearly understood. From the answers obtained by the experiment, it is understood that one-fourth of the subjects suffer from the understanding the clothing pattern which is the prerequisite for this experiment, and answered with incomplete understanding. The common thing among these subjects is that they took the action "to select the same number for all patterns belonging to the same genre, because detailed classification". As the , responses gathered to patterns that people who are not specialized in clothing design are easy to imagine (such as pants and dresses). On the other hand, the pattern selection situation of people who were not suffering from understanding of the

Figure 3.5: Generated images around 43000 iteration. We show these images to subjects and ask them to classify these images to patterns.

pattern was dispersed, and a combination of various patterns. In addition, there was an opinion that it is difficult to recall clear clothing designs from ambiguous images such as “they do not know the details”, “they might have imagined if the image was clear”. From the above, we think that it is difficult for ordinary people who don’t learn pattern making classify ambiguous generated images to pattern. Moreover, the influence on the clear design was not recognized in this experiment. Next, I researched whether the patterner can identify the design of these generated images and whether it is possible to produce patterns from these generated images.

Chapter 4

Implementation of Clothes Prototype

4.1 Drawing Patterns

Seven partcipants(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 Figure4.3, the second pattern was asked to draw the pattern based on the image selected by each subject (shown in Figure 4.4). 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.

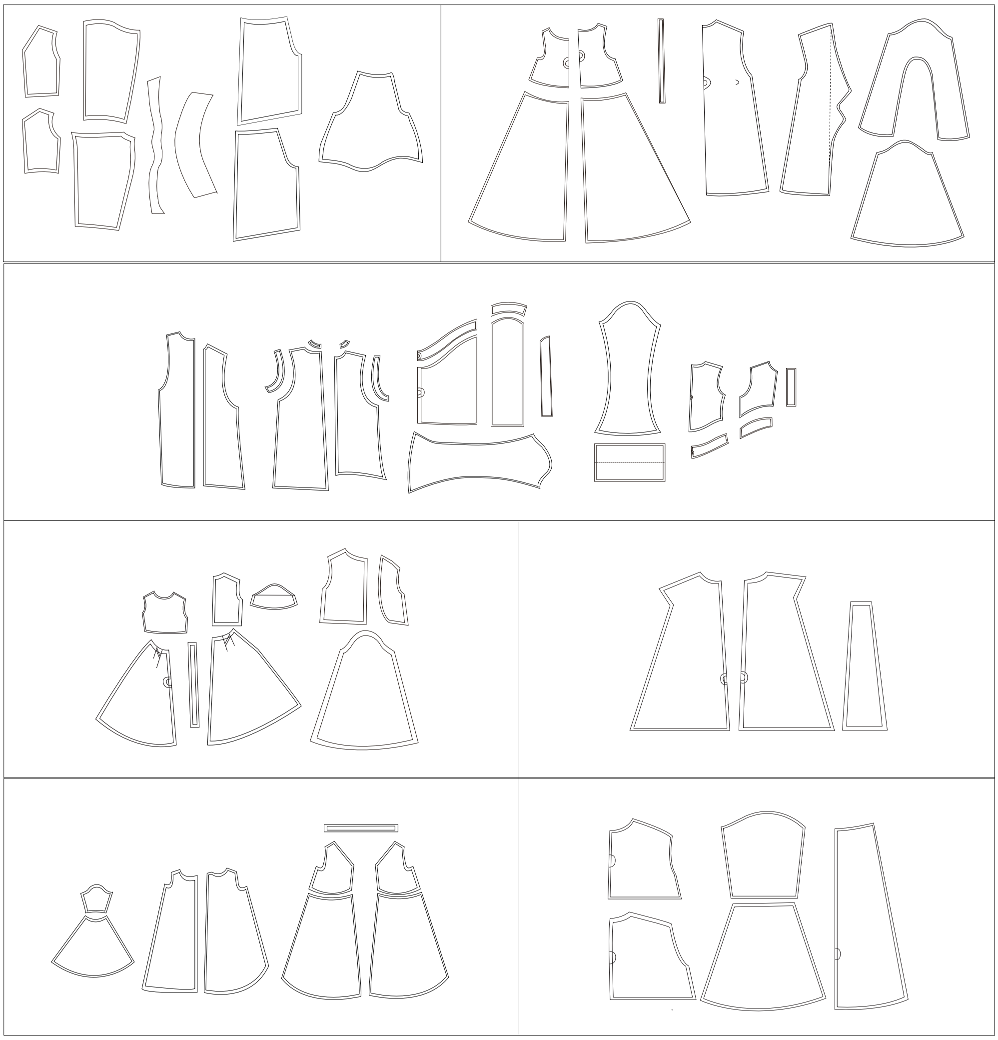


Figure 4.1: Pattern from A

Figure 4.2: Pattern from B

One patterner said *"At the beginning there was no detail of the image, so I was anxious to draw a pattern. I was allowed to do it freely, so I made a design with an image that I saw obediently and tried to make it a pattern. I felt it was new because I had never done it before, and it was fun. I am looking forward to waking it up in shape."*

(P1: Female, 22 years, design experience 5 years)

Another patterner said *"Frankly speaking it is quite funny. Since the design picture is blurred, it is fun to do that design myself."*

(P2: Male, 21 years, design experience 1.5 years)

And another patterner said *"When drawing a pattern at a company, designers decide the design and I often draw patterns accordingly, so my consciousness not much enter the drawn pattern, but the design picture of this experiment is a big silhouette, I can decide details with imagination so drawing patterns is very creative and very fun."*

(P3: Female, 23 years, design experience 5 years)

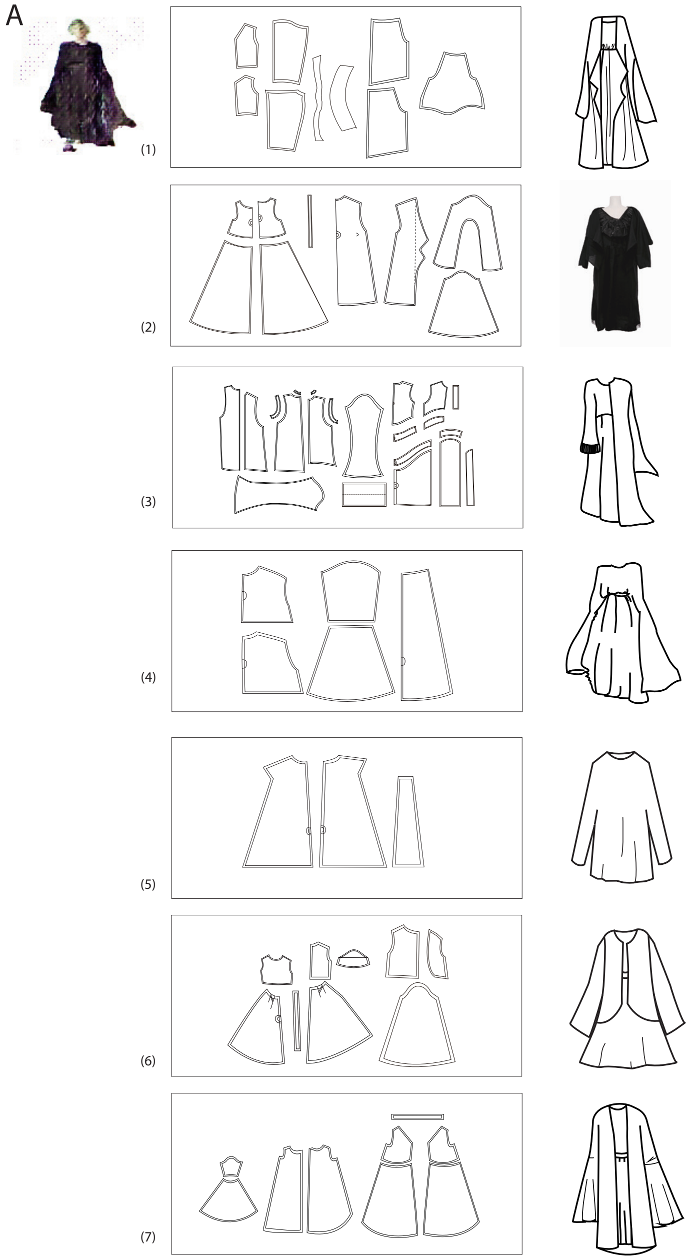


Figure 4.3: A patterns are drawn from same image by each patterners.

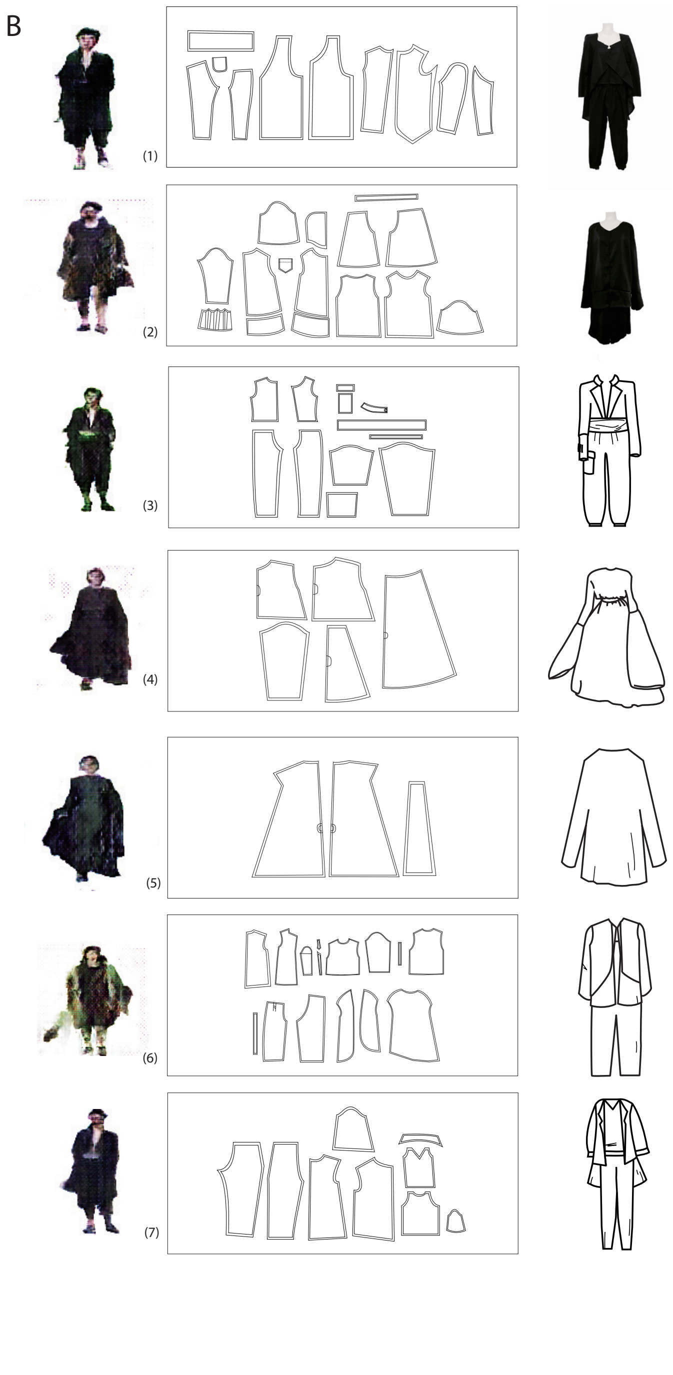


Figure 4.4: B patterns are drawn from what patterners selected

To summarize these opinions, imagining from generated images and drawing clothing patterns is a work process that they have never done before. Hence, many patterners had the impression that this process was pleasant. Also, as the resolution is coarse, the patterners seemed to fun because they needed to design detail freely. The other subjects, there were also subjects asked for clearer images.

"Regarding deep learning, I think it would be better to be able to extract clearer images."

(P4: Female, 22 years, design experience 4 years)

In order to make the design more concrete, there were also subjects who responded that not only the image of the front but also the image of 360 degrees could produce a pattern closer to the image as a pattern.

It was very difficult for me who self-educated design studies to design an image from a blurred overall image and to create it in a pattern. However, I think that I could design very freely in a sense. When clothes detail was displayed at 360 degrees, I thought it would be much easier to make a pattern closer to the image!

(P5: Female, 22 years, design experience 3 years)

Next, we showed patterners all of these patterns, and we took a questionnaire on what they thought.

I feel that there is a big difference on the center part with what I drew which is very well understood. Even in the same image, I felt that the way of how the image and design are perceived were different such as when the number of patterns that are clearly different. The number of patterns is large due to the fact that the number of items in men's is large, but personally it was very interesting that the patterns are different in each image even with the same ladies' image.

(P5: Female, 22 years, design experience 3 years)

I think that it is possible to create patterns of each persons even if I draw a pattern in the case there is a good design picture, but since the design picture in this experiment was mosaiced, we can think of various kinds of patterns.

(P2: Male, 21 years, design experience 1 and half years)

Most of the lengths and silhouettes are similar, but I often thought "Indeed, there is such an idea" about that switching and design details are quite different compared to other patterners. The number of parts of the pattern was completely different, I felt it was interesting.

(P1: Female, 22 years, design experience 5 years)

4.2 Making Clothes from 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.4.6shows images of clothes. A (1) and B

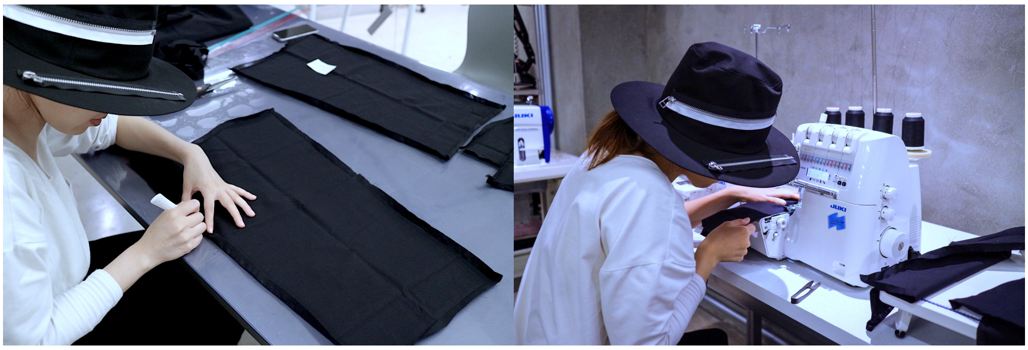


Figure 4.5: Making clothes from patterns.

Figure 4.6: Our system's output clothes.

(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 4.7: Evaluated clothes. (2), (4), (9) are actually sold learning source brand clothes. (3), (6), (8) are our input. (1), (5), (7) are other brand clothes.

4.3 Experiment on Clothes

4.3.1 Qualification and User Reaction

We conducted an experiment to evaluate whether the image generated from Deep Learning can be instruction sources for creating a new clothes. The experiment is comparing and evaluating the quality of the actually sold clothes on market with our clothes and the other brand clothes. In the second experiment, we evaluated the quality of the actually sold clothes on market with our clothes and the other brand clothes.

4.3.2 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.

4.3.3 Experimental Design

We prepared images of the source brand and output of our method and clothes images of other brands, respectively three. To the subjects, six clothes of the source brand were first exemp lified (shown in Figure 8). 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).

	clothes1	clothes2	clothes3	Ave.
Original Clothes	4.0	3.8	3.6	3.8
DeepWear	3.8	2.7	3.3	3.2
Other Brand	2.5	2.4	3.0	2.7

Table 4.1: The of the questionnaire that to distinguish the source brand clothes.

4.3.4 Drawing Patterns

The patterns that the patterner drew based on the image we specified are the Figure 4.3, and drew based on the images selected by each are the 4.4. 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. The common feature of the drawn one-piece dress was the spread of the hem was spreads widely. Therefore, A, many people recognized them as one piece, and it turned out that a pattern of a similar type was drawn. In B, (4) and (5) are judged to be a one piece and the number of patterns is small. Likewise, patterns drawn by subjects with a pattern of experience years of 5 years floated the idea up to relatively minute detail, actually causing the design as a pattern. Generally, when drawing patterns, patterners role is to produce clothes designed by designers as they are in their design, faithfully as patterns. Therefore, in the pattern creation process, the intention of the patterners will not be included in the pattern. However, since the generated images don't have clear resolution, the patterners had to produce pattern based on the coarse quality images. But we thought it was the process of making a new fashion, because it seems important for a patterner to design his own idea to design.

4.4 Results

An weighted averages of these s are shown in the Table4.1. 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 (Table4.1: (3)) and the clothes of the actual learning source brand. The reasons for the respondents who judged them similar to the learning source brand were as follows.
About the original brand, *Loose solid black cloth.*

(P1: Male, 23 years)

The looseness is similar to the brand clothes.

(P2: Female, 24 years)

I felt that the balance of the length and sleeve was close to the image example.

(P3: Male, 20 years)

The opinion about (3) *It is loose, the fabric seems good.*

(P4: Male, 23 years)

Because hem length is long.

(P5: Female, 22 years)

As above, they judged from the silhouette and size feeling, the whole atmosphere and the cloth texture. As a reason why the numerical value of image (6) which is clothing made by our system is low, we give opinions of respondents.

It is too feminine.

(P6: Male, 23 years)

I feel that the detail on the chest is different.

(P7: Female, 22 years)

I feel the decoration is strange.

(P8: Male, 23 years)

I feel loose silhouette but the decoration of the chest is conspicuous so the impression is different from the example clothes.

(P9: Female, 24 years)

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

I think that the judgment criteria of similarity or dissimilarity are mainly the length and the whole image. I thought that those with a center of gravity in the upper body would not be 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 specific brand have oversize, straight line, and big silhouette image is very similar because the waistline of other companies' brand products has been narrowed down.

(Patterner 1: Female, 22, design experience 3 years)

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 2: Male, 21, design experience 1 and half 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 4: Female, 22, design experience 5 years)

4.5 Discussions

4.5.1 New Design Process

In the process of general fashion design, the designer first writes a design drawing, and based on that designer, the patterner draws a pattern drawing from the designer and creates clothes based on the pattern drawing. After that, put it on a fashion show, get a feedback on that fashion show, make a pattern again, making clothes... it is a feedback loop. In this research, we propose a method to receive new feedback by adding image generation by deep learning to the process of receiving a feedback from the fashion show and reworking the pattern. By experiments, clothes made by machine learning is I could not tell the brand from clothes. Therefore, it became clear that there is a possibility of succeeding brand design. Even after the death of the designer, design can be inherited by making clothes based on the generated image which extracted features of design by machine learning. However, this time, I chose a single color that is easy to capture features of design brands by machine learning. I think that whether we can firmly extract the features of other brands by machine learning will be the keys for the future.
Moreover, In this process, obtaining design inspiration easier for designers is thought to be extremely important in modern times where design cycles are becoming faster due to the prevalence of fast fashion. With modern fast fashion cycles, cycles become faster, and clothes often enter the market without being designed well. Therefore, by incorporating our method, there is an advantage in that it can receive feedback from the image. Also, one of the features of fast fashion is that the price is very cheap. It is an advantage for consumers. However, from the selling side, it is hard to make a profit. If we can use AI for design, we can reduce personnel expenses, so it would be easier for profits to arise even if we lower the price.
On the other hand, for patterners, they could make clothes patterns without designer's rough sketch. patterner's work is making the design of the designer in patterns.

4.5.2 Images

In this study, we used brand clothes that are easy to understand the feature in the data set. As a result, the output clothes also became clothes that captured the features. If you use clothes that do not feature much in the data set, the output clothes will also have no features, and it can not be determined whether learning was successful. However, if you exclude the purpose of learning the characteristics of the brand, fashion design itself can be generated by deep learning, so the objective of supporting the design of the designer can be

achieved.
As a problem, the image quality is low. If we can run the learning using a higher-performance image generation method than DCGANs, combining super resolution technology or using more high-performance GPUs, increase the size of the images and the quality will be better, we can display the details of the clothes more finely. There will be no process of making free designs in the process of pattern creation by patterners, caused by the roughness of the image, but it is possible to create suggestions on concrete designs from generated image. Then it may be able to substitute the design picture of the clothing production process which is currently being done normally. Also, it is also may be possible that even people without general clothing experience may be able to do fashion design from that image. Also, in experiment 1, the subjects who did not have clothing experiences can recognize the image clearly, it is thought that classification of the clothes pattern becomes easier from the image. With this, we think that even people without clothing experience may be able to get inspiration of fashion design.
When learning the data set, it was necessary to resize to a square image. Therefore, there was a possibility that the aspect ratio of the dataset original image could not be learned. Given that the s of this experiment have been successful, it can be considered that clothes that do not matter the aspect ratio from the image could be inferred by a patterner that generates a pattern from this generated image.
In the project to reproduce the paintings of Rembrandt8, we incorporated information on the unevenness of the picture and geometric information on how to draw the face, and let AI create a picture. This time I learned with a 2D image, but as I was told that it would be nice to have a 360 degree clothing image in a patterner, if you can generate images on the other side or learn in 3D, It is thought that clothes faithful to the generation can be created.

4.5.3 Copyright

It is thought that there will be copyright problem. There is no legal problem in using this data set or creating clothes in this research. However, with this system, there is also the risk that products are made without permission to the source brand and fakes will spread. However, as fake sales now become a problem even now, even after the death of the designer, the fashion design that succeeded the design will be able to be done than that problem. We believe that it is important to have the advantage of being aware. Therefore, if we can prevent misuse, we think that it is meaningful in that creativity can remain in future generations.

4.5.4 Material

Since the silhouettes of the clothes change depending on the cloth material, when producing clothes according to the DeepWear system, we found that we can make them closer to the ideal clothes by using the same kind of fabric of the cloth.

Chapter 5

Implementation of Image Generation for Patterner

5.1 Generative Adversarial Networks

The Generative adversarial network consists of a generator network G and a discriminator network D. Given training d ata 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 $V(G, D)$.
Progressive Growing of GANs (P-GAN) [42] technique is popular from last year. The main idea of P-GAN is to gradually and symmetrically grow generator and discriminator in order to produce high resolution images. P-GAN begins with a very low resolution image (4×4), the quality improves for each new layer in the model, and fine-grained detail is added to the image generated in the previous stage. Promising results were obtained in the experiment of the CelebA dataset [43]. We employ P-GAN to generate 128×128 and 256×256, 512×512 pixel images using our specific brand runway dataset as training data. We follow the same experimental setup and structural details of the original P-GAN article [42].

5.2 Training

We collected images of a specific brand [7] announced between 2014 and 2017. We used web scraping Python code to create the training dataset. As the , over 1000 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 512×512 (dataset is uploaded as supplemental material).
We implemented our network with Chainer[1], a deep learning framework. We followed implementation and training procedure recent work by Karras et al.[42]. Training was done with a batch size of 2, using Adam with hyperparameters (α=0.0002, $\beta_1 = 0$, $\beta_2 = 0.99$,

[1] `https://chainer.org/` (last accessed September 10, 2018)

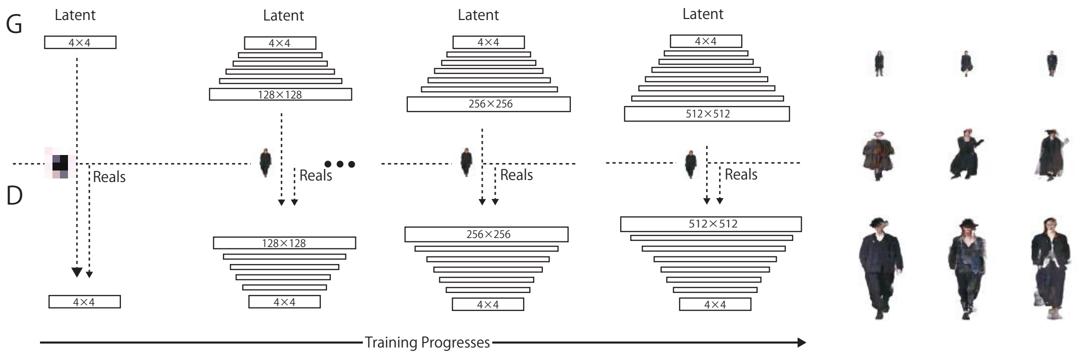


Figure 5.1: Our training begins with both generator (G) and discriminator (D) with low spatial resolution of 4×4 pixels. As training progresses, layers are gradually added to G and D to improve the spatial resolution of the generated image. All existing layers remain trainable throughout the process. Here, it refers to a convolution layer operating with $N \times N$ spatial resolution. This enables stable synthesis with high resolution and greatly speeds up training. One shows each three example images generated using progressive growth of 128×128 and 256×256, 512×512 pixel images.

$\epsilon = 1e - 08$). We run 3 types of epochs (500, 1000, 1500) on an NVIDIA Titan V100 GPU in order to evaluate the quality of the each epochs generated images in later experiments.

5.3 Experiment on Generated Images

We examined the relationship between resolution of images generated by GANs and the number of epochs, which is the learning time of GANs, to the ease of pattern making. Also, in order to evaluate how interpretation of images changes based on individual differences, we asked them to self-evaluate their knowledge about the learning source brands.
Three of generated images, 500, 1000, and 1500 epoch, three levels of resolution 128px, 256 px, and 512 px, each of which reflects the learning time of the generated image, total 27 images, and each generated image is randomly arranged one by one randomly for each subject. We conduct the survey through Google form and made a 5-point evaluation of 1 (no pattern can be drawn) to 5 (well subtracting pattern) (Figure 5.2). After 27 images evaluation, we asked about how much knowledge of the learning source brand design and pattern do they have, 1 (absolutely unknown) from 5 stages (I know very well).

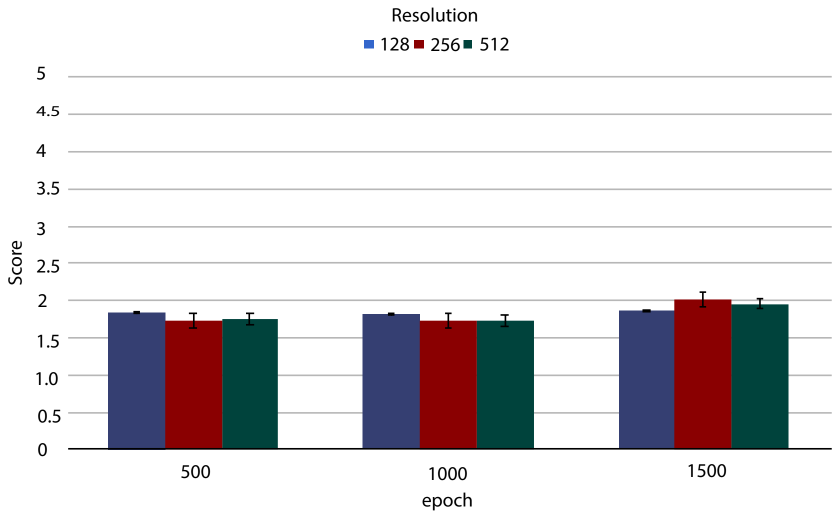
5.3.1 Participants

We recruited professional pattern makers from pattern makers crowdsourcing site. Fifteen participants (12 females, 3 males) participated in the experiment. All participants are experienced as a professional pattern maker. The participants' length of service as a pattern maker was between 3 and 39 years (M = 19.36, SD = 12.5).

5.3.2 Results and Statistical Analysis

Results are shown in Figure 5.3. We used SPSS Statistics version 24 for analysis. First, we analyzed interaction effect between resolution and epoch with two way ANOVA. The

Figure 5.2: Generated images shown to participants. Three images each combining the conditions of 128px, 256px, 512px, 500epoch, 1000epoch, 1500epoch were showed and evaluated the ease of pattern drawing in five stages. 27 images are evaluated by each participant.



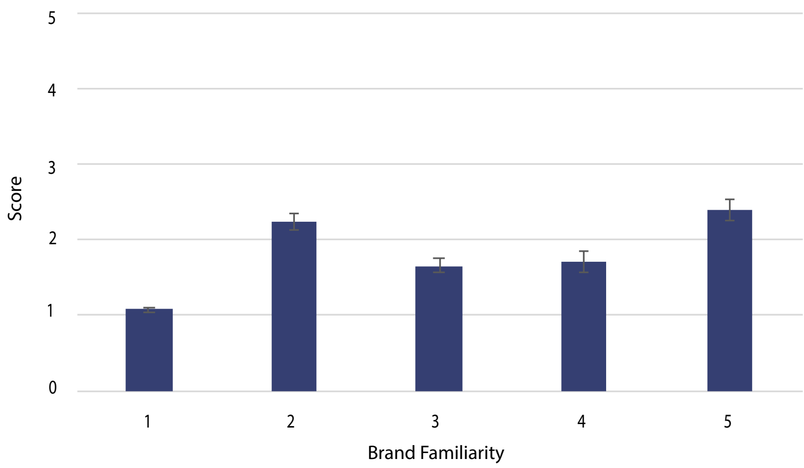


Figure 5.3: (Top) of the questionnaire response resolution and epoch. (Bottom): Pattern maker's knowledge about learning source brand.

sphericity assumption was supported by Mauchly's test of sphericity at the 5% level, or the degrees of freedom were corrected using the Greenhouse-Geisser estimates of sphericity. A comparison of epoch and resolution showed no significant interaction effect ($F(4,188) = 1.166$, $p > 0.05$). Second, we analyzed main effect of resolution and epoch respectively with two way ANOVA by fixing one side. By fix resolution, epoch showed no main effect ($F(2, 94) = 0.052$, $p > 0.05$). Post-hoc Bonferroni test suggested significant difference at 256px, between 500epoch and 1500epoch, and 1000epoch and 1500epoch ($p < 0.05$). There was no significant difference in other combinations of epochs. From this point, with the exception that there is a significant difference when the resolution is 256 px, since the main effect was not observed at every other resolution, we interpreted epoch do not affect the score of ease of drawing the pattern.
By fixing the epoch, resolution showed main effect ($F(1.835, 86.265) = 5.501$, $p < 0.05$). Post-hoc Bonferroni test suggested no significant difference for any combinations of resolution for any epochs ($p > 0.05$). At this point, with the exception that there is an increment in resolution, because the significant difference was not seen, we interpreted resolution do not affect the score of ease of drawing the pattern. Because there is a main effect, there is a possibility that a significant difference may be obtained if the resolution is made higher, but any meaningful maybe offset because it requires a large amount of calculation resources to output an image with a resolution exceeding 512 px. Also, it is obvious that the details will be unrecognizable if we look at images with very low resolution. Because of this reason it is difficult to make clothes using small images, so there is no need for 64px or lesser resolution comparison.
Finally, the influence of pattern maker's knowledge was analyzed by one-way ANOVA. shows a main effect of pattern makers knowledge score ($F(4,427) = 22.2$, $p < 0.05$). Post-hoc Tukey's HSD test suggested knowledge score showed no significant difference between score group 2 and group 5, and group 3 and group 4 ($p > 0.05$). There was significant difference in other combinations of knowledge score ($p < 0.05$). From this point, ignoring that there is no significant difference between 2 and 5, and 3 and 4, knowledge affect the score of ease of drawing the pattern.

From these results, we found that the ease of pattern drawing from generated images depends on knowledge of pattern maker, and lesser on the quality of generated image.

5.3.3 Patterns Makers Opinions

We interviewed the paticipants who have a pattern making experience with the brand of the learning source and concluded that it would be easier to draw patterns from the generated images as they had an average score of 2.8 or more.

(Patterner 1: Female, 31, design experience 10 years)

Because there is accumulation of shapes of silhouettes and patterns that I have came up with patterns that I have been making with the brands up to now, it may seem easy to understand even if it is a rough design image. Judging that it does not resemble any shape of the past clothes, arranging it while obtaining inspiration from the generated image, I had to think about how to draw the pattern. 1, 2, 3 in 5 stages have a high dependence rate of patterner's design (the rate of leaving the design to myself), while 4 and 5 show the ratio of the design of the generated image to the pattern design which is around half to half.

5.4 Discussions

In the experiment, the ease of drawing the pattern from the generated image by GANs was evaluated by factors such as resolution and epoch. Analysis of the interaction effect between resolution and epoch using two way ANOVA showed no interaction. Next, when we take a test for each factor, epoch did not show main effect, but resolution showed main effect. However, there was no significant difference in multiple comparisons on resolution. From here, there were no thresholds for each of the three levels of resolution and three levels of epoch numbers, and it turned out that when drawing a pattern from the image, it is not related to the quality of the generated image.
Next, since the influence of pattern maker's knowledge was significant among almost all groups, we found that what is important when drawing a pattern from a generated image is pattern maker's knowledge.
Therefore, it is more important to have pattern makers with prior knowledge to the brand design and brand pattern than the quality of the generated image. From this we can deduce that in the clothes production, there is not much need to spend computation resources to increase the resolution of the generated image instead more resources should be directed to pattern makers selection.

5.4.1 Pattern Makers

In fact, in our workflow, images are generated with a specific brand as dataset, patterns are drawn from the image by pattern maker, and clothes are made by sewing craftworker. It is important to treat both excellent professional pattern makers with collection brand experience and the selection of cloth used for sewing as two important elements. Professional pattern makers with collection brand experience have the ability to draw more complicated and detailed patterns than professional patterners who without the experience. In the fashion world, clothings are more like an art piece than just a garment in the famous show such as Paris collection. The collection brand's pattern makers are often found interpreting the designer's intention from the abstract designer's sketch and they would then make the pattern expressable in the form of clothes that you can actually wear. Since the pattern makers are the one with the skill to materialize the designer's sketch, it is possible to draw complicated and detailed patterns based on the intention of the brand in the situation of drawing patterns from abstract images generated by machine learning. On the other hand, pattern makers who are not experienced in collection brands shows patterns of clothing designs that are not composed of general and complex lines, so the range of expression in pattern design is reduced compared to the experienced ones. Therefore, it is difficult to draw a pattern that is faithful to the original brand's clothes from the features extracted in rough image. Therefore, it is more likely for the experienced pattern makers of collection brands to be able to draw the patterns from our generated image.
From here we elaborate based on the opinions from the pattern makers. Pattern maker of the original brand, who has been in service for 10 years, first focuses on the characteristics of the parts of the clothing and identify it as a category such as V-neck, skirt, jacket, pants etc. . Then, combined with what the pattern maker has produced so far, he would draw a pattern that is relevant to the source brand. As it is also shown in the s of the experiment, it is important that one have experience in making the clothes of the learning source brand.

Also, typically, the sketch picture in fashion design has a lower abstraction level than the generated image and more specifically instructed to the features of the brand and designer's intention. Among the very experienced pattern makers, we received positive opinions such as the degree of freedom is high and interesting in pattern production from the abstract generated image. In other words, the higher the abstraction level in the generated image, the greater the proportion of ideas of the pattern maker exerts on the drawn pattern, which the dependence on pattern makers experience and skill will increase. In contrast to design, patterns typically require high quality with numbers of realistic scales to produce clothes , so patterns can hardly be automated. Therefore, we propose that pattern makers are the most important aspect in drawing pattern from highly abstracted generated image.

5.4.2 Dataset

From the learning source brands, we found that it is easier to output s that match the brand image using a source brand with a certain unified design that does not change drastically every season. Therefore, the idea of drawing a pattern by combining a generated image with the brand image and brand design is increasing. In this paper, we used the dataset of a certain brand [7] image. The reason for using this brand's dataset is that the generated images are easier to recognize because of the obvious brand features. This specific learning brand, both men's and women's, all season black, is a brand that is unified with a relatively oversized silhouette design. Therefore, when clothes design is included in the data set, the color of commonality is high, and it is easy to extract the features by a machine learning. If learning is performed with brands that do not have recognizable features that are easy to understand, there is a concern that designs that inherit the characteristics of source brands can not be created. Moreover, in case where designs of all seasons of both men's and ladies' are not unified, extraction of features is difficult by machine learning, ing difficulty in brand identification. Therefore, when extracting features by performing image generation of a specific brand, it is considered better to use brands of relatively unified designs as source learning brand. In terms of generating an image that inherits the features of a designer's work, within the scope of the experiment conducted this time, it is not possible to extract the potential features that are unrecognizable by human eyes with machine learning. It also means that human resources such as pattern makers are as equally important.

5.4.3 Generated Images

Evaluation of images generated by GANs is a difficult problem. When comparing the dataset and the generated image by mean squared error or PSNR, there is a problem that a blurred image tends to be generated[44]. In addition, even if an image with a bad score is generated numerically, it sometimes looks beautiful when people see it. In general, evaluation of the generated image of GANs is done by Inception score[45] etc, but this time we can not use Inception score because we prepared the dataset ourselves. Good indicators should be proposed so that scores of images that look beautiful when viewed by humans, and can be used for a wide range of dataset.

5.4.4 Cloth

When making clothes with one brand's design creation image like the image we generated this time, the selection of cloth is also an important factor to obtain the characteristic.For example, clothes based on the same pattern Even if you make the cloth, if you use cloth of hemp material and hair goba, hemp dress becomes thin, material is flickering design, drape becomes a beautiful silhouette design. If you use polyester gaba, it is a material with tension on the fabric and it is difficult to stretch, so it will be designed to keep the line beautifully. In other words, to make final clothes output that make the most of the goodness of design and pattern, selection of cloth is a very important factor. If we select the optimized cloth based on the generated image and pattern automatically by machine learning, we think that we will make clothing optimized for design, pattern, and place and occasion when wearing.

Chapter 6

Conclusion

6.1 Summary

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. According to the of questionnaires whether ordinary people can imagine patterns from generated images, it is shown that ordinary people can not classify clothes from the generated images. Next, 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.

Also we reveal that it is more important to invest in pattern maker selection than computer resource when making clothes from abstract generated images. When a pattern maker draws a pattern using an abstract generated image by GANs, resolution and epoch number are not the most important factors. It was found that it is possible to draw a pattern from the generated image of lower quality by a pattern maker with prior knowledge of the source brand. Therefore, from the viewpoint of cost performance, it was found that it is better to cost a pattern maker with source brand design knowledge and experienced pattern drawing than to invest in computing resources to improve the quality of the generated image. The reconfirm the importance of pattern makers in the process of making clothes.

6.2 Future Work

Since the number of data sets and computer resources are limited in this research, the resolution of the generated image and the number of epochs of learning are limited. It is difficult to gather sufficient data by web collection only to gather data sets with uniform conditions such as the position and background of the model that is the object with just one brand of clothes. However, by securing enough computer resources to gather hundreds of thousands of datasets and to converge learning using that dataset, the degree of capture of the resolution of the generated image and the features of the brand is improved , The conclusion may change. Also, although it is possible to draw patterns even from low-resolution images with few learning times, increasing the number of learning times improves the quality of feature extraction in designs, and moreover, it is possible for brands and designers used for data sets An image that captures the features of the design is generated, and for a parameter called a degree of agreement with the characteristics of the brand, there is a possibility that a significant difference appears in the epoch number. There is room for discussion as to whether pattern automation can be automated by machine learning.In other words, in this flow, it can be said that it is possible to generate a pattern from the generated image. In addition, it may be possible to automatically generate a pattern tied to the generated design image by learning pattern data and sketch image as bilateral translation. In order to realize this, a large amount , It is necessary to construct a scheme that can obtain large quantities of pattern data drawn on the paper which is usually discarded as an intermediate product in digitally processable form. By making all of the generated image, pattern generation, and cloth selection automatic by machine learning, the production cost of expensive clothes such as highly designable collection brands suddenly lowers, production of high quality clothes in the world Becomes possible. It is conceivable that a big revolution will occur in the fashion industry.

Acknowledgement

We would like to expess my appreciation to my supporters. I couldn't have written master thesis without the support of my friends and family. Special thank you to Occhi, Sato-Sensei, Sayan-Sensei, Aoto-San, Jyun, Yuzuha, Otao, Oomori, Soneo, Muramatsu, Minatatsu, and Mama.

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