Punch Card Knitting Pattern Design in Collaboration with GAN

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Abstract

Punch card knitting codifies the different stitch patterns into binary patterns, informing the knitting machine when to change color or to generate different stitch types. This research explores the collaboration with Generative Adversarial Neural Networks (GAN) to generate new punch card pattern designs. Reflecting on the creative collaborative approach to working with artificial intelligence for design. The hypothesis is that AI can learn the basic underlying structures of the punch cards and the pattern underlying structures that is inherent to Fair Isle knitting. Using a dialectic process of curating data sets, to re-configuring data post processing, AI and human design both play a role in the creation of these new patterns. Utilizing Style GAN2, the results from these explorations offer different insights into pattern design and generate new unique designs from the latent patterns. Ultimately the designs are physically tested on a domestic knitting machine, resulting in novel fabrication methods to produce AI designs as a physical result going beyond just the typical computer-generated image.

Introduction

Graphic patterns are all around us, in nature, in mathematics, and in textiles. These patterns are made of repetitive shapes and geometries. Textiles are associated with patterns, as many designs emerged based on the structure of weaving and knitting (Stewart, 2015). Knitting uses a single yarn looped around itself in rows, and to make patterns, multiple colored yarns can be knit together. Similar to the Jacquard loom for weaving, domestic knitting machines use punch cards as a basic binary pattern telling the machine to knit either color "A" or "B". Most knitting machines come with a set punch cards, and more punch cards can be purchased separately. Images of these punch cards can also be found on the internet, providing a sufficient source for a data set in this research. See Figure 1.

AI is modeled after the human brain, and it is proven successful at learning and understanding patterns in data sets. This research explores what AI can learn from a data set pertaining to knitting punch card images. The hypothesis for this research is to generate new knitting pattern designs using Style GAN@ trained on images of punch cards as a database. These new patterns will result in a collage and distortion of a variety of styles, cultures, and histories from this input data. The results from the StyleGAN2 training are images. These images are then translated into physical punch cards that could be used to fabricate knitted test samples. The results reflect on what can be learned from the knitting patterns designed with AI, revealing the underlying structures of all the patterns based on the input dataset.

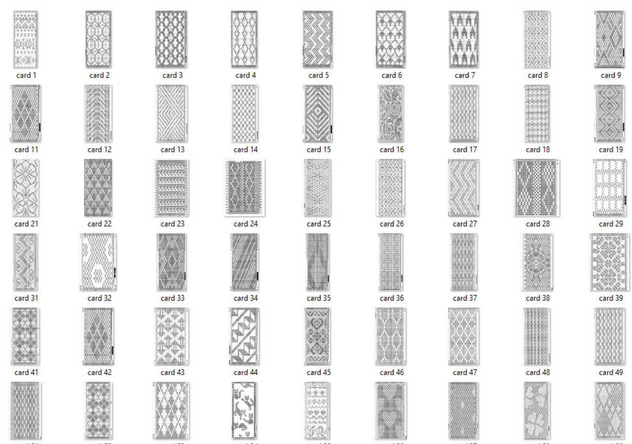

Fig 1. Sample Portion of Punch Card Data Set.

The collaboration between the computer and the human designer is in the curation of the data set and selection of viable results. This has inherent bias, as to what images are available on the internet to use for the data as well as certain taste and styles that may be more likely selected by the designer. The GAN algorithm learns from these images and generates results. The human in response learns from those results and adjusts the inputs and weights in the algorithm, to control the creation of knittable patterns and aesthetically pleasing patterns. The research addresses the importance of the history of textiles in computation and goes beyond the textile community as these results begin to discuss a larger question of design computation, ornamentation, craft, and the creative process in collaboration with AI.

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Context

Historically textile design has been largely a female dominated craft (Barber, 1995). Meanwhile the computer industry has recently seemed to be more male dominated (Lee, 2019). Although there has also been a long history of textile artists using computers and the feedback loop between the two modes of working (the Center for Craft, 2020). Such as in the works by Janice Lourie, Sonia Sheridan, Lia Cook and others.

Even early computers are based on textile industry. Joseph-Marie Jacquard in 1800's invented the Jacquard-loom, allowing for complex weaving patterns to be made using punch cards (Essinger, 2007). In developing early computers that utilize binary code, Charles Babbage and Ada Lovelace adapted the use of punch cards for their Analytical Engine (Essinger, 2015).

This is one way the history of punch cards, computation, and textiles is interrelated. Furthermore, with pixels, these the early 8-bit computer graphic images are similar to the pixel like designs generated with knit stitches in knitting patterns. Using artificial intelligence as a way to design new textile patterns combines these old and new methods of textile creation and computing together in a contemporary way.

Computational Textile Design Precedents

There are precedents of designers and artists who have worked with algorithms and AI for knitting, sewing, and embroidery. These examples show some of the development for computational textile design.

Neural Networks have been used for various textile designs, such as for the color selection and pattern design for new embroidery samplers. In this case, a sentence was input into an Entertainment AI that adapted the sentence's content into the color selection and motifs for an embroidery sampler design (Smith, 2017).

Another example of knitting being explored with generative AI design is through the development of using neural networks to generate CNC knitting machine patterns. This example generates knitting patterns from images of unknown knit material by being trained on the structure of several sample knits and their corresponding patterns, resulting in a user-friendly interface called img2prog (Kaspar, 2019).

Alternatively, hand knitting patterns are written out in a shorthand language, referred to as knit-speak. In the skyKnit project a natural language learning AI was trained on 500 patterns to develop new knit-speak directions for hand knitting patterns. Using the online community of Raverlry.com these patterns were physically knit by artisans and crafters; the resultant designs were ultimately very strange looking (Shane, 2019).

These examples show the development of computation within textiles and design. Eventually, creating actual physical manifestations of the crafted knit work is essential. Currently, so much of AI designs happens and remains within the computer and this research hopes to use AI for pattern design to bring the design into the physical world with physical constraints.

Knitting Patterns

Patterns are repetitive, symmetric, geometric, and balanced; our human brains are for some reason attracted to them. Gestalt theory attempts to outline some of the principles such as the orders of symmetry, figure-ground, similarity, and common fate as ways to describe how our minds begin to understand patterns as a whole before they recognize the specific elements (Koffka, 2013). Psychologists are still studying the ways that our minds process these patterns.

Since neural networks are modeled after how our brains learn, artificial intelligence predictably should understand the specific rhythms, symmetries, geometries, and spacing that make these knitting patterns. Although Neural Networks are learning these patterns from localized relationships, our brains recognize the overall patterns. This sets up an interesting dichotomy as the task is approached in opposite ways, but the results are potentially the same.

Punch card knitting patterns interoperate a traditional knitting style called Fair Isle. Its origins are credited to Scotland's Fair Isles, as it is a popular knitting pattern technique in that region. Fair Isle patterns are recognizable by their basic geometric shapes, small-scale repetition, mirroring, and simple color changes that never consist of more than two colors per row. See Figure 2.

Fig. 2. Example Fair Isle Knit Pattern.

While one color is used as activate stitches, the other colored yarn floats in the back. Floats should be no longer, than three to five stitches in a successful Fair Isle pattern (Pulliam, 2004). The switching off and on between colors creates a pattern through pixel-like imagery as each stitch acts like a pixel of color. The use of only two yarns at a time makes this knitting technique ideal for the binary codification into punch cards, although this limits the types and styles of possible patterns that can be generated. Furthermore, Fair Isle knit pattern punch cards have an almost 1:1 relationship with the image of the punch card, this provides an easy starting point to design AI knit patterns as the designer can visually see the potential design in the punch card results before having to test knit the patterns.

Punch Cards

Domestic knitting machines were popular between the 1940s until the 1980s. The hobby has since decreased in popularity, resulting in many of the companies that sold knitting machines and punch cards no longer producing them. However, there are many images of punch cards and patterns available online.

A standard punch card is 24 dots or stitches wide and about 60 stitches long. When knitting the patterns can be repeated in the vertical direction and in the horizontal direction to create larger knit fabric pieces.

There are three main types of Fair Isle patterns: geometric patterns, organic or floral patterns, and object-based imagery.

For this project the database of knitting punch card images was generated by image scraping from Google and incorporated all the different styles. These images were sorted manually to affirm the best quality of images for training, culling out images that are un-clear, low resolution, images of knit material rather than punch cards, and images that are not straight on. This process resulted in a concise set of data of black and white legible punch card images. See Figure 1.

This sorting could generate bias, as certain images that were removed may have been interesting patterns but were removed based on image legibility.

In order to generate a more extensive set of data from the small data set of quality images collected, the punch cards were cropped down into smaller sections. As punch cards have a defined width but an undefined length, the various lengths would cause issues in training, thus cropping them into equal sized images would produce more consistent data set. Each image was cropped into square proportioned images, resultantly showing 24 dots by 24 dots of the punch card. These images consisted of overlaps between them. This cropping of the images is a common technique as the GAN training we are interested in the localized relationships rather than the overall pattern design.

Mirroring was also used, as well, since punch cards do not necessarily have a front or back and can be fed into the knitting machine facing either direction. Therefore, some of the asymmetrical punch cards were fed into the data set facing multiple directions.

This achieved a final set of about 1200 punch card images for training. Although, with in this data set, bias may be hidden within the Google Images as the search results from what is available on the internet. Perhaps certain patterns may appear more frequently than others due to cultural popularity and preference. The image searches were also run in English language search terms, and knitting patterns from English websites would come up more frequently than those from other languages. This could favor certain styles of patterns that are more popular with in English speaking cultures. In addition, Fair Isle style is from the United Kingdom, thus many of the patterns designs created have a western sensibility and are represented in the cultural significance of these patterns. Many patterns, such as polka dots to stripes, have certain cultural meanings and historical significance, but they can be different meanings in another culture (Stewart, 2015).

This research does not hope to look at one culture over the other or to remove cultural significance from these patterns. It attempts to perhaps understand and learn the deeper localized relationships of geometry and proportions that generate patterns across cultures and meaning.

Furthermore, to understand the underlying structure of the punch cards, for the specific constraints in Fair Isle knitting, such as not to have long floats. The pattern should also be repeatable; it would need to have balance across the card rather than be weighted to one side or the other. Furthermore, the knit is constructed in rows, and each row can exist independently, but a successful pattern has vertical and horizontal repetition and geometry.

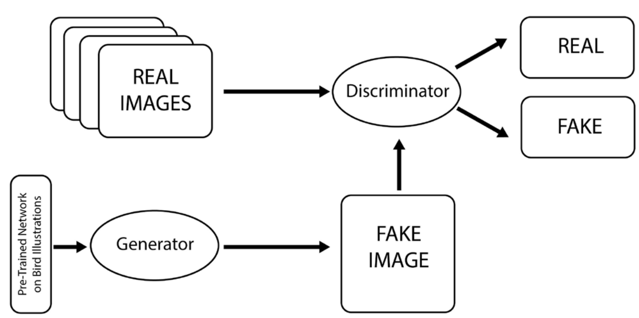

Fig. 3. Diagram of GAN.

StyleGAN2

StyleGAN2 was released in early 2020 by NVIDIA, and it is an update to the earlier StyleGAN developed in 2018. Generative Adversarial Networks (GAN) consist of two neural networks, one which generate images and one that test the images (Karras, 2020). StyleGAN2 learns the characteristic artifacts in a data set of images to produce new images.

The GAN first generates images from a random noise pattern while the discriminator tests them and feeds back information to the generator to correct it. Each time the data set is processed is an epoch, in which the generator gets closer to the desired results until it eventually the generated images can fool the discriminator into believing that the image is real image. See Figure 3.

In this study the data set was uploaded to a base model of StyleGAN2, pre-trained on bird illustrations. Several tests were run at different ranges of epochs. Through this the designer is able again to curate and collaborate with the GAN to select various weights and adjust the influence of the training. Although StyleGAN2 is a supervised learning, even more control is given to adjusting the settings.

In this project at around 1500 epochs, the images started to begin to look like new punch card designs. At less epochs the designs still consisted of splotches of solid black from the originally trained bird illustrations. Where training longer 1500 epochs, the model began to face mode collapse. The punch cards generated at this point began to look all self-similar, and the individual dot matrix was became lost. This is most mode collapse likely due to the data set being too small and self-similar. Another cause could be failure to converge. Further investigation of this could be explored into what may cuase these failures.

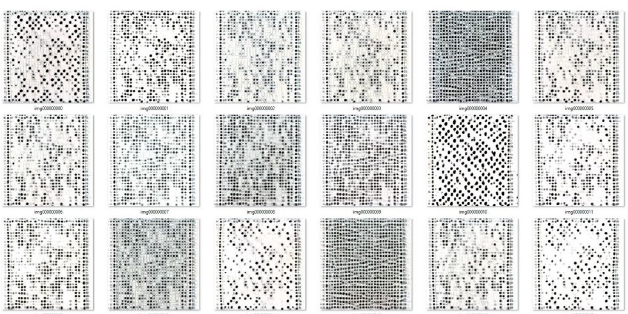

Fig. 4. Image Results from StyleGAN2 Training.

Ultimately, the results from 1500 epochs was a set of 50 successful sample images. The images appeared to have the basic structures of punch card designs. The designer could judge the success of these images based on their appearance to look like other known punch cards. See Figure 4. Since these images were in the square format, three images close in aesthetic quality were selected and combined vertically to create a punch card pattern in the similar proportions of a typical punch card.

In the resulting images there is a variety of differences between images with a high density of dots to ones that were relatively sparse. Some patterns seemed very random while others had clear underlying diagonals, checkers and other patterns embedded within them. Although these that appeared random at a glance, it did have some underlying structure revealed upon further reading and inspection. Patterns did emerge, such as checkered patterns and diagonal stripes and vertical designs. These types of repeated structures can be seen in many of the input patterns from the data set.

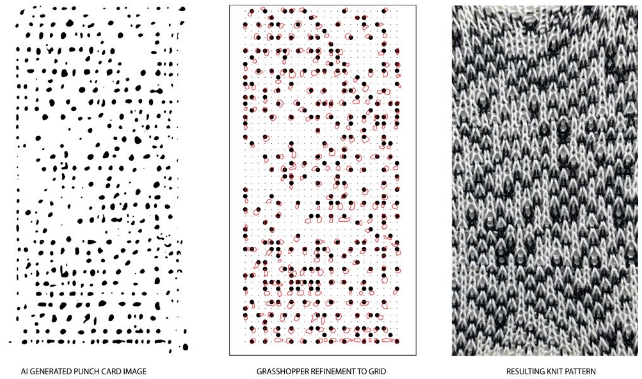

Fig. 5. Translation of image training to Knit Results.

Results

After the designs were digitally generated, physical punch cards were made. The image results from each of the methods was not clear enough to directly use as a punch card and needed to be processed. Grasshopper for Rhino was used to trace the large, clear dots from the images into vector line work, which was then organized on the grid structure by moving these circles to the closest grid points. See figure 5.

The patterns were then laser cut out of thick Mylar to make them into usable punch cards for the knitting machine. They were then used to knit on a Brother KH836 Domestic Punch Card knitting machine with a standard 4.5mm gauge. Since the punch card pattern is only 24 stitches wide, this would result in a small pattern of only four inches wide. Therefore, the pattern was set up to repeat once in width. This created an eight-inch by eight-inch test swatch of material, allowing it to knit once vertically through the pattern design.

Two different colored yarns were used to visually and texturally make the pattern apparent. Physically knitting the patterns gives a better understanding of the successes and failures of the Fair Isle knitting punch cards, as they could be tested with material constraints of the different yarn types and the physical knitting process.

Physical Knit Results

The StyleGAN2 training resulted in a range of outputs, consisting of images with very dense dots to very sparse dots. Some of the sparse dot patterns were potentially going to have an issue, as there were some rows with only one or two changes in color, resulting in very undesirable long floats. Although, these patterns did result in having other features such as clear vertical and repetitive structures. See figure 6.

The denser StyleGAN2 generated patterns were more successful punch cards as they had adequate spacing for short floats, consisting of lengths under six stitches. In addition, because the pattern changed colors so often it is difficult to tell that the pattern is repeated more than once horizontally which is quite successful. This pattern was more of an overall discrete dot hatch or fill between the two colors rather than an image-based pattern. The resulting pattern ultimately has a certain movement to it as it resonates between the different diagonals and checkered designs. See Figure 7.

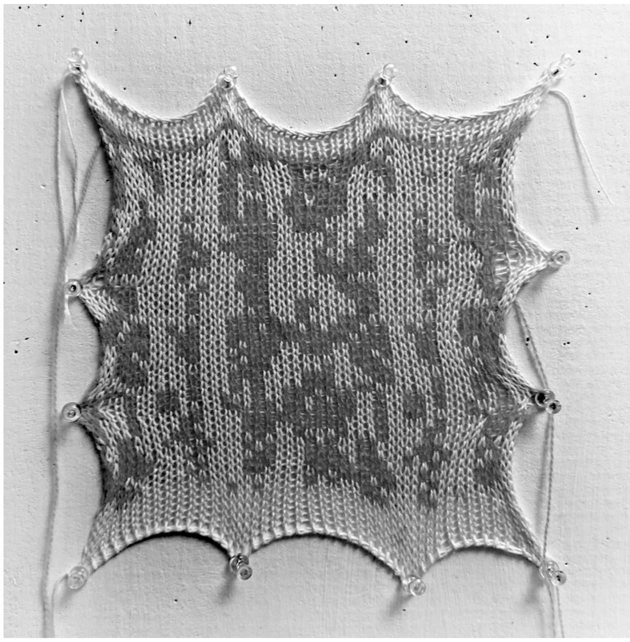

Fig. 6. Results StyleGAN2 Pattern example 1

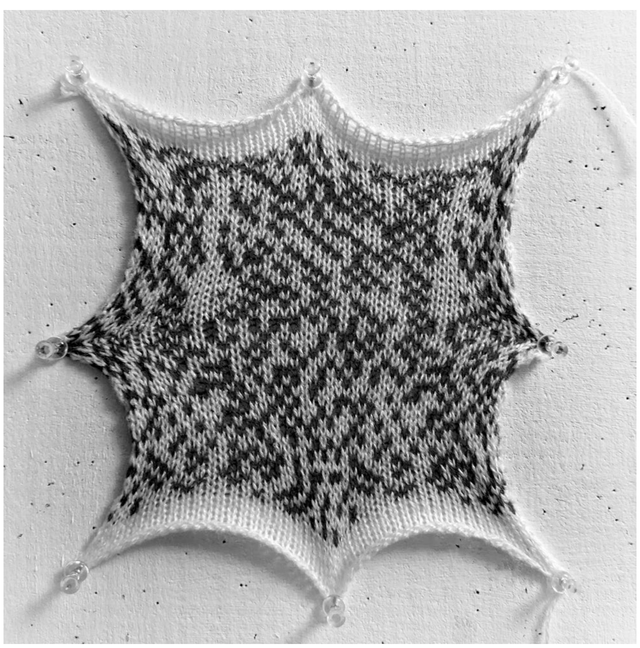

Fig. 7 Results StyleGAN2 Pattern example 2

Patterns Results Compared to Random

Although the patterns resultantly look random at first glance, they represent a binary pattern of 24 by 24 dot matrix the possible number of patterns is 2^(24x24). This is an extremely large amount. Subsequently, if a random binary code generator was asked to make an array of 576 numbers there would be no logic as to how these numbers may arrange on the 24 by 24 punch card grid. As well, the results may lead to possibilities where there is only one dot in a full array of 0's. These types of imbalanced results from a completely random pattern wouldn't generate successful knitting patterns.

This suggests that the resultant patterns which may look random are far from it. That there are learned qualities about proportion of dots, spacing of dots, as well as not having too many or too little in a row.

Furthermore, these patterns look random at first glance but further study and inspection of both the punch card, and the knits do show that there are clear successful underlying structures learned. They had a noticeable clear structure of diagonal pattern and checkered patterns, disrupted by some random stitches. This is possibly because the data set had a lot of diagonal patterns in it. Additionally, these geometries work well for the constraints of Fair Isle knitting and the knitting machine functions.

It is difficult to fully tell whether these underlying patterns are really existing or whether it is the human brain is just imagining patterns where there are none. The Gestalt theory supports the ideas that our brains are wired to find patterns, structures, and logics in the world around us to help us make sense of our surroundings.

Conclusion

Each of the resulting tests developed unique patterns that never existed before. The results did have success, and there were clear underlying structures that each of the training method could understand and replicate patterns that seemed to fit within the constraints for Fair Isle knitting.

Throughout the process the human and the computer collaborated. First, the designer worked to search and curate the data set. Next, the data set was too small, therefore it needed to be multiplied. This was done by cropping the images into multiple smaller images and mirroring the images, to generate a larger data set for training. Then, the human designer also collaborated when running the StyleGAN2 training specific weights and epochs were tested to get the desired results further supervising this training. Finally, once the images were output from the training they still need the designer to select and reconfigure the images into longer ones to make typical knitting punch cards.

Since the images were also not perfectly clear, Grasshopper and Rhino were used to re-configure and refine these images into usable punch cards. The knitting was then all done by the human craftsman. This process uses a lot of back and forth collaboration between AI and algorithms to design and create these new punch card patterns.

Resultantly, the neural networks learned the patterns underlying structures, which has noticeable features from the styles in the existing dataset. These underlying structures worked to create visual appeal that are essential to the knit material's tectonics as well as the principals of patterns that For the development of this research, there are still opportunities to have more control over the data, such as inputting specific pattern types such as only the geometric patterns, or testing punch cards with tuck or lace patterns rather than Fair Isle.

These patterns also have further potentials as to how they can be utilized in real world situations as fashion, décor, or architecture. The possibilities to combine ornamental patterning with functional aspects of using different materials for texture and material proper changes such as elasticity are the next phases of this design research.

These patterns ultimately combined the structures and mish-mashed the cultural significance behind these zigzags, dots, and diamonds into something new and designed computationally with collaboration between human designers. This serves as a reflection on our historical significance of textiles and computation as well as posing the design potentials of the new age of AI and technology in our daily lives.

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