Project Proposal

Deep Learning Design Generation and Application in Fashion

Aaliyah Hänni
MSDS Student

Dwight Sablan
MSDS Student

Liem Luong
MSDS Student

Vanessa Joy Hsu
MSDS Student

Tatiana Teppoeva
Microsoft Sponsor

University of Washington | Master of Science in Data Science
December 15th, 2021

Table of Contents

Introduction

Art and data science - on the surface it looks like there is no correlation between the two fields. Fashion and neural networks - the relationship between the two may not be clear. Travel back in time, the history of digital art and technology started in the '60s. In the old days, there were challenges with limited computing resources and the power to blend Art and AI for a meaningful result. Any accomplishment at that time was considered a significant success in the art field. As technology advances year by year, the application between Art and AI gets closer. In reality, art and fashion are the inspiration for people to come up with new pieces of art. Advanced machine learning in the data science field enables creativity to make this process more efficient and more accessible to the broader audience. That is where the two fields meet to make our life more enjoyable. In this project proposal, we share our plan for leveraging deep learning in the data science field to create new types of art: an AI-generated pattern.

Problem Statement

In the fashion industry there is a constant demand for new and interesting design patterns, which can often be expensive and time consuming to create. Fashion designers are bound by their own internal biases and have limitations on the level of creativity and in-demand fashion that they can create within a given timeframe.

Currently, the influence of the fashion industry is dominated by a select few designers, which makes fashion design not easily accessible to average people. On average a pattern maker "… will charge from $80 – $750 per pattern depending on design complexity" (Quick Answer: How Much Should I Charge For Designing Clothes?). The time that it takes to generate a new design pattern varies greatly but is found to take an average of about 2 months (How Long Does It Take To Manufacture Custom Clothing?).

Neural networks can be used to alleviate some problems in this field by improving the level of creativity in design for both quantity and quality outputs. In this work, we explore some latest Neural Network methods in machine learning to generate new fabric (color and shape) and improve the model performance. Our solutions based on AI could be easily used by non-tech savvy and will make design creation more accessible for the broader audience.

Background

The fashion industry is one of the industries that demand for new products every year. Just like the tech industry, consumers expect to see new phones, tablets, and gadgets every year. In fashion, consumers expect to see new design patterns and new trendy outfits every year. The demand cycle of new designs is quick especially for seasonal clothing. With open trade, companies can implement mass production and ship products around the world throughout the year. However, the fashion industry possesses a unique problem: The pool of good designers is small for a large market demand, the cost of new pieces of custom design is expensive and not affordable to an average consumer, and finally the time it takes generating new designs is not fast enough. With advanced technology in machine learning and automation, this adds a booster in terms of efficiency and productivity for many industries. Fashion industry can benefit from this technology as well. Many AI applications have been developed and implemented in the fashion industry over the decades. In this project, we plan to focus on developing a neural network model which can learn from the textile pattern (color and shape) and create an AI-generated pattern.

Current pattern generation tools mostly involve pre-designed patterns that can be customized by the user through specifying colors and/or morphing shapes. These tools require more effort from the user, and are limited in what they can create. Tools like Wombo Dream (https://app.wombo.art/) allow users to create AI-powered artwork by specifying a prompt and an art style. While this tool does a great job of creating new, unique artwork, the images it generates are not directly applicable to clothing. Our project aims to marry these two ideas to allow users to use AI to generate unique clothing patterns based on custom inputs.

Data Pipeline

We will be using a dataset containing images of clothing patterns from a public github repository (https://github.com/lstearns86/clothing-pattern-dataset) for our minimum viable product. This dataset is free to use without restriction. It's available to us in CSV format and consists of 2750 images of clothing patterns grouped into six classes: solid (419), striped (534), dotted (315), checkered (492), zigzag (407), and floral (582). In addition to the classes and images, the dataset comes with 8 other features: original width, original height, crop X, crop Y, crop width, crop height, and scales. These features will be used to reconstruct the images in the dataset. In addition to the images in the CSV file, the dataset also contains 400 fabric pattern images in PNG format, grouped into their respective patterns by folder location. We will be using Jupyter Notebooks to import and experiment with the dataset.

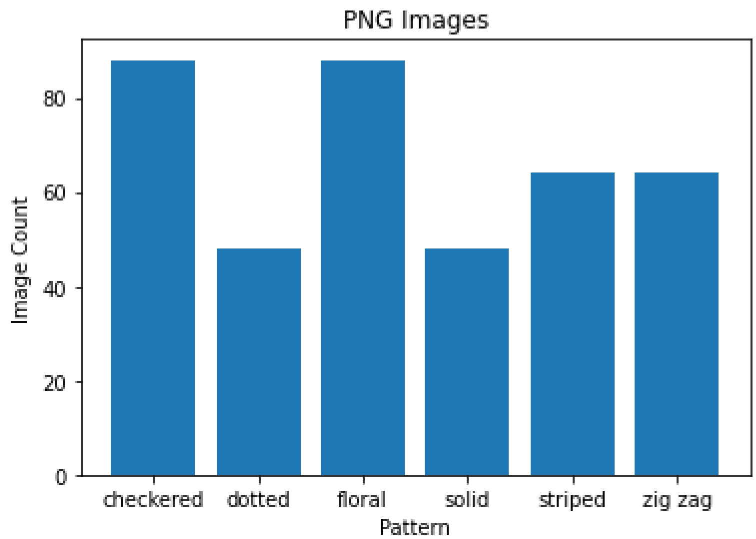
Data Exploration

Dataset Summary

The dataset we used consists of two types of data: fabric patterns images in PNG formats, with the different patterns grouped by folder location (referenced as PNGs Images) and an excel sheet of URLs of pattern images that can be downloaded as JPGs (referenced as URL Images).

PNG Images

All of the 400 PNG images are standardized to the same height and width (640x640 pixels), have a consistent resolution, and are segregated into one of six folders that defines the image pattern (checkered, polka dotted, floral, solid, striped, and zig zag). Below displays the distribution of image counts in each pattern.



URL Images

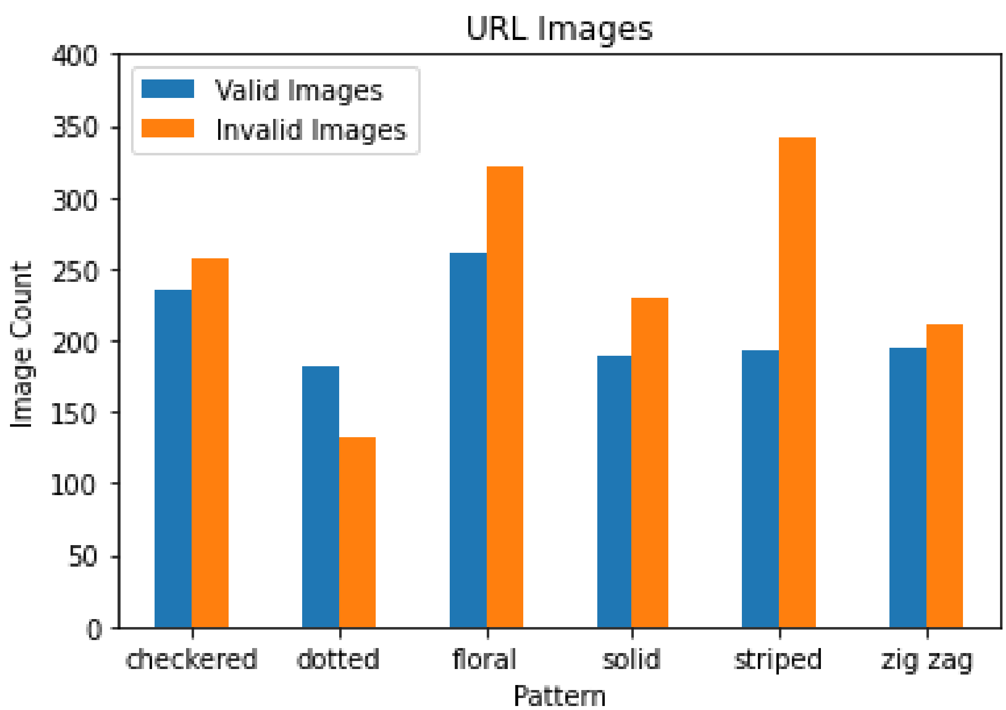
The second part of this dataset is an excel sheet that lists 2749 JPG image URLs available to download from the internet. The dataset contains the following features for each image:

Dataset Features

- *Class Name* (object): The associated image pattern categorization, it is one of six categories (solid, striped, polka dotted, checkered, zig zag, floral)
- *URL* (object): The URL path to the image source, where it can be downloaded
- *Original Width* (int64): The original width of the image, in pixels
- *Original Height* (int64): The original height of the image, in pixels
- *Crop X* (int64): The center of the image with respect to the horizontal axis, as defined by the author, in pixels
- *Crop Y* (int64): The center of the image with respect to the vertical axis, as defined by the author, in pixels
- *Crop Width* (int64): The author recommended width to crop the image to, in pixels
- *Crop Height* (int64): The author recommended height to crop the image to, in pixels

Dataset Distribution

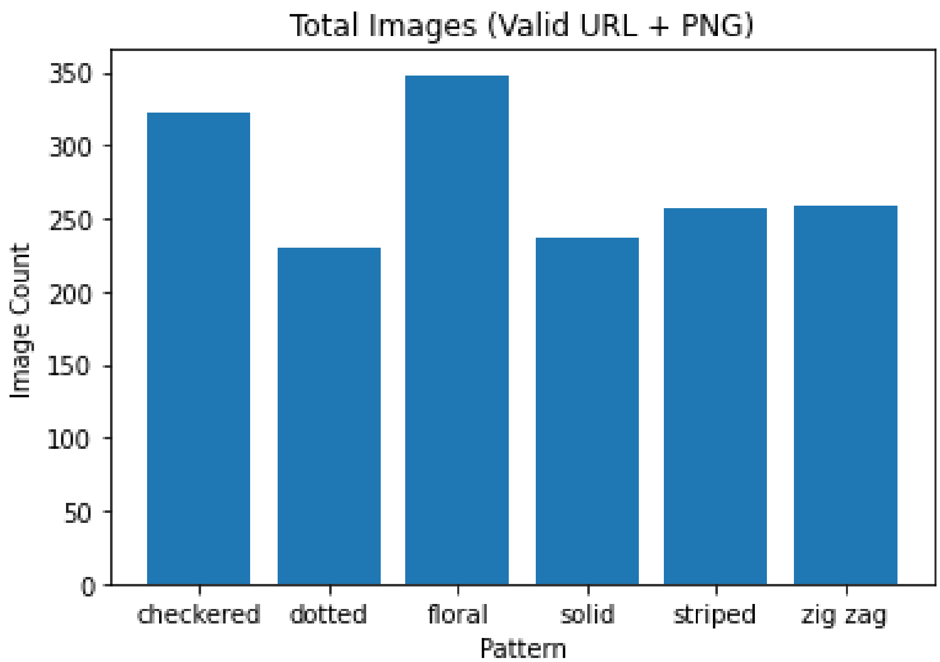
The URL image dataset contains 1495 broken or invalid URL images that could not be downloaded and 1254 images that we were able to successfully download. Below shows the distribution of valid and invalid images available by pattern type.



The smallest image is 225x225 pixels, whereas the largest is 6016x6088 pixels. The mean image size (before cropping) is 927x829 pixels and the standard deviation of this image size (before cropping) is 834x695 pixels. It is worth noting that the mean and standard deviation of the width and weight were calculated disjointly.

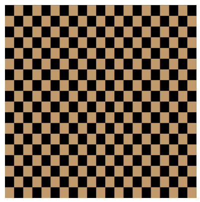
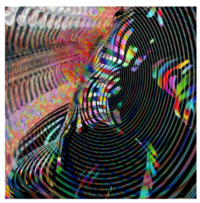
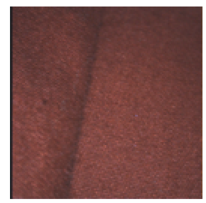
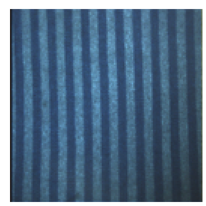
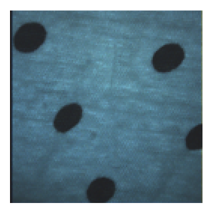
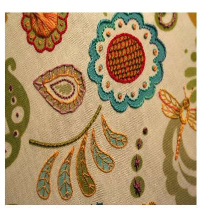
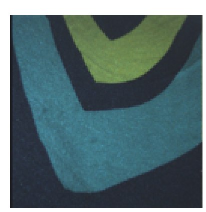
Data Preprocessing

For this project we will use a combination of the supplied PNG images and valid URL images. There are several preprocessing steps that we performed to merge the datasets into a final data frame of standardized images, and their associated pattern category. First we extracted and downloaded the valid URL images, using a standard naming convention, so that all images are labeled by their pattern and a unique number (for example: *floral_01.png*). To standardize the images to all be standardized size of 224x224 pixel images, we centered each image using the Crop X & Crop Y, and cropped each image using the Crop Width & Crop Height columns in the dataset, as "... one author manually removed erroneous results and cropped others as necessary (e.g., to remove logos or background imagery)" (Stearns, 2018). All of the PNG images are already in a square format, but had to be reduced from 640x640 pixels to 224x224 pixels. This yields a final dataset of 1654 images, with each category containing a range of 230 - 348 images, all of size 224x224 pixels, the distribution of categories is shown below.



Data Integrity

The URL images have a much better resolution and diversity of patterns, but do not follow a clear or consistent definition of pattern categorization. The authors described that to create the dataset, they "... added the word 'fabric' after each class name and downloaded the top 1000 search results from Google Images" (Stearns, 2018), which means that there is no integrity of the pattern category. The PNG images are more consistent and reliable, but contain the same pattern from multiple angles, so there is a lot of duplicity. Another issue is that the PNG images are all low resolution and include folds and stains in the fabric. Examples of images from each dataset are shown below.

Pattern	**URL Images**	**PNG Images**
Checkered		
Solid		
Striped		
Polka Dotted		
Floral		
Zig Zag		

Proposed Solutions

Deep Learning Framework

We consider two popular deep learning frameworks, TensorFlow and PyTorch. Ultimately, we decided to use PyTorch for our project given several considerations. Briefly, PyTorch is a popular deep learning framework that was developed by Facebook's AI Research lab (FAIR) in 2016. It is an open source library for the Python programming language used to develop deep learning applications in computer vision and natural language processing. PyTorch has grown in popularity for its simplicity, ease of use, efficient memory usage, and flexibility. One of the main reasons we chose to use this library over TensorFlow is that it is integrated well with the Python language whereas TensorFlow is less of a pythonic framework and more of a new language. Additionally, performance in PyTorch is optimized automatically via parallelism where the intensive computational work during the training process is distributed among multiple CPU or GPU cores.

Model

For our minimum value product, we plan to develop a supervised deep learning model that produces a unique and interesting pattern. If time permits, another aspect of our "nice to have" features include a model that will generate different and unique sewing patterns.

Website

We intend on building a website as a "nice to have" feature. Upon completion of our model, should time allow, we will create a website that will allow users to interact with it. The first stage of this website will focus on pattern generation. We will allow users to customize their design preferences (e.g. stripes, florals) and output a pattern based on their inputs. They will be able to download the pattern as an image file to their own devices, and use it as they wish. Further "nice to have" features on our website will include visualizing the patterns on some items or on AI generated sewing patterns - given we are able to complete this model.

Risks & Benefits

Risks

When it comes to training a machine learning model, there are always risks to take into accounts. For our project, some potential risks that the team identified are worth mentioning:

Baseline model risks

- Neural network is highly dependent on the dataset. Risk of users not being able to generate a pattern that they wanted because it is not available in the training dataset.
- There are several areas of potential bias in our image dataset. One concern is the number of duplicate patterns shown in the PNG image dataset, having duplicate images means that our model has potential to overfit a specific type of one pattern, and may not have the ability to create diverse or creative patterns. In the URL images, some images are not reliable and do not appear to follow any clear definition of pattern, and even the authors of the dataset admitted that, "[o]ur use of a single online source does introduce some bias in our dataset, which future work should investigate " (Stearns, 2018).
- Risk of introducing bias into the output pattern because each person can have different opinions on what is a "good" or "nice" pattern. Diversity in cultures also poses a bias of how users view the end-result pattern.

Nice to have features risks

- Integration of the model and website can introduce some challenges, such as being able to efficiently run a model in the backend on a front-facing website.
- There are still some concerns on how we will be able to train a neural network model on clothing shapes, and how to teach the model to create 3 dimensional patterns using images.

Benefits

Creating a model to generate new patterns, designing a website to interact with the model outputs, and potentially training a model to generate new fashion outfits has many benefits. Some of benefits from working on this project:

- We create an algorithm that generates new design patterns, with significantly less time and cost as traditional methods.
- Our model will create patterns that are unique and interesting, and have a captivating story of being generated by machinery, rather than humans.
- Team gains knowledge and experience from working with a sponsor who has past experience in this neural network art. It is an interesting field in data science with a lot of applications in life.
- Experiences gained by the team working on a real world data science project from the beginning to the end.

Schedule

Project Milestones

1. Develop a Neural Network Model that creates new design patterns.
   Goal completion date: 1/31/2022
2. Optimize model performance and make it available to users.
   Goal completion date: 2/28/2022
3. Create our final report and poster to share what we accomplished.
   Goal completion date: 3/10/2020

2022 January

MON	TUE	WED	THU	FRI	SAT	SUN
					1	2
3 Team Tag Up (6 PM @ Zoom)	4	5	6 Team Tag Up (6 PM @ Zoom)	7	8	9 Sponsor Tag Up (12 noon @ Team)
10 Team Tag Up (6 PM @ Zoom)	11	12	13 Team Tag Up (6 PM @ Zoom)	14	15	16
17 Team Tag Up (6 PM @ Zoom) **Milestone Track 1**	18	19	20 Team Tag Up (6 PM @ Zoom)	21	22	23 Sponsor Tag Up (12 noon @ Team)
24 Team Tag Up (6 PM @ Zoom) **Milestone Track 2**	25	26	27 Team Tag Up (6 PM @ Zoom)	28	29	30
31 Team Tag Up (6 PM @ Zoom) **Milestone Track 1**	Notes Track 1: Develop the machine learning model and perform testing Track 2: Develop the website 01/31/2022 - Plan to have a working NN model by end of month					

2022 February

MON	TUE	WED	THU	FRI	SAT	SUN
	1	2	3 Team Tag Up (6 PM @ Zoom)	4	5	6 Sponsor Tag Up (12 noon @ Team)
7 Team Tag Up (6 PM @ Zoom) **Milestone Track 2**	8	9	10 Team Tag Up (6 PM @ Zoom)	11	12	13
14 Team Tag Up (6 PM @ Zoom) **Milestone Track 1**	15	16	17 Team Tag Up (6 PM @ Zoom)	18	19	20 Sponsor Tag Up (12 noon @ Team)
21 Team Tag Up (6 PM @ Zoom) **Milestone Track 2**	22	23	24 Team Tag Up (6 PM @ Zoom)	25	26	27
28 Team Tag Up (6 PM @ Zoom) **Milestone Track 1**	Notes Track 1: Continue to work on improving the NN model, add new feature Track 2: Integrate the NN model with the website and testing Track 3: Start to writing the report and poster on the week of 21st of the month 02/28/2022 - Plan to have both the NN model and website integration done					

2022 March

MON	TUE	WED	THU	FRI	SAT	SUN
	1	2	3	4	5	6
			Team Tag Up (6 PM @ Zoom) **Milestone Track 3**			Sponsor Tag Up (12 noon @ Team)
7	8	9	10	11	12	13
Team Tag Up (6 PM @ Zoom) **Milestone Track 3**			Team Tag Up (6 PM @ Zoom) **Milestone Track 3**			Sponsor Tag Up (12 noon @ Team)
14	15	16	17	18	19	20
Team Tag Up (6 PM @ Zoom)			Team Tag Up (6 PM @ Zoom)			Sponsor Tag Up (12 noon @ Team)
21	22	23	24	25	26	27
28	29	30	31	Notes		
				Track 3: Final report and poster 03/03/2022 - Draft report ready for sponsor 03/10/2022 - Finalize report and poster		

Our Team

Vanessa Joy Hsu

Aaliyah Hanni

Liem Luong

Dwight Sablan

Vanessa Joy Hsu

- Team role: Software/Web Designer & Developer
- Experience: Vanessa is a student in the University of Washington's Master of Science in Data Science program and a systems engineer at AT&T. In her day-to-day role, she analyzes data and uses machine learning to improve findability and user experience for an internal data platform. Her background in software engineering will assist her in leading the software design and development efforts for this project.

Aaliyah Hänni

- Team role: Team Lead
- Experience: Aaliyah is a master's student in the Master of Science in Data Science at the University of Washington and a Data Analyst for JH Kelly, where she leads a team of developers, testers, and analysts for developing modules for internally created software. It is these experiences that motivate her to take the team lead position, in which she will assist in communication, coordination, organization and documentation of this project.

Liem Luong

- Team role: Machine Learning Engineer
- Experience: Liem is a student in the Master of Science in Data Science at the University of Washington. He is currently working at Boeing, where he leads the technical development of a forecasting system. He also leads the project management of the annual long-term forecast – Commercial Market Outlook. His background in data analytic and his passion for the machine learning field will assist him in this project. He looks forward to learning from and sharing with his teammates.

Dwight Sablan

- Team role: Data Engineer
- Experience: Dwight is a recent graduate of the University of Guam with a Bachelor of Science in Mathematics. His most recent work experience includes being a mathematics adjunct instructor and a research associate in biostats at the University of Guam. As a research associate his responsibilities included data processing and statistical analysis for Pacific Island Partnership for Cancer Health Equity. Some of the projects he's worked on includes examining the ethnic disparities of diabetes prevalence and liver incidence on Guam, estimating the prevalence of obesity among children on Guam, and evaluating the effectiveness of tools to educate and encourage individuals about colorectal cancer screening.

Cited Sources

How long does it take to manufacture custom clothing? Intrepid Sourcing & Services. (2021, December 3). Retrieved December 9, 2021, from https://intrepidsourcing.com/trade-wiki/how-long-does-it-take-to-manufacture-custom-clothing/.

lstearns86. (n.d.). *Lstearns86/clothing-pattern-dataset: A large dataset containing images of clothing patterns*. GitHub. Retrieved December 1, 2021, from https://github.com/lstearns86/clothing-pattern-dataset.

Quick Answer: How Much Should I Charge For Designing Clothes? Outrightdigitalmedia.com. (n.d.). Retrieved December 9, 2021, from https://outrightdigitalmedia.com/qa/quick-answer-how-much-should-i-charge-for-designing-clothes.html.

Stearns, L., Findlater, L., & Froehlich, J. E. (2018, October 8). *Applying Transfer Learning to Recognize Clothing Patterns Using a Finger-Mounted Camera*.