

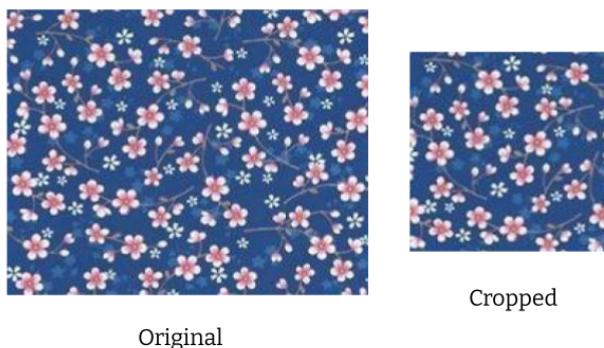
Generating Media Sequences

Goals

This project looks into generating patterns that can possibly be used for designing textiles. Markov models are useful for predicting unknowns and generating the next step based on the one before. It would be interesting to see how this works on a dataset of patterns. For this project, a folder of floral prints has been curated from images on Pinterest.

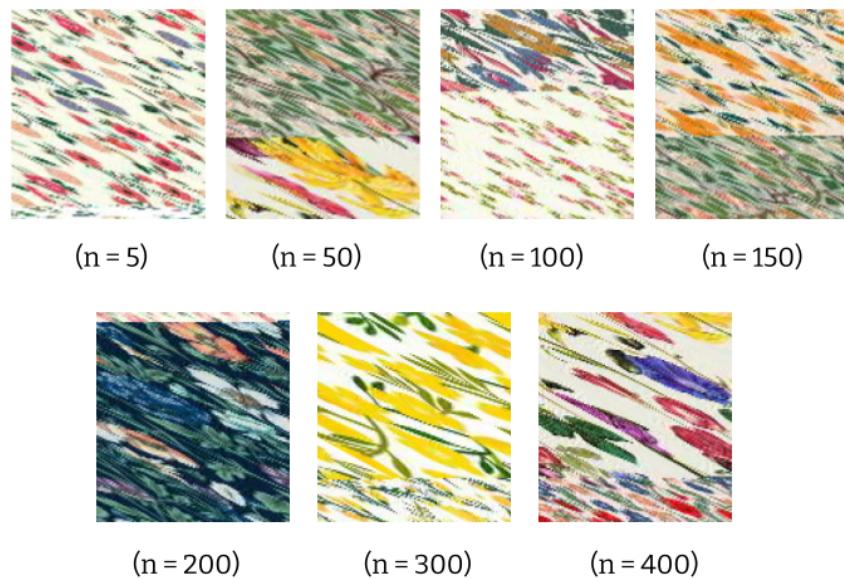
Exploration

There was trial and error originally as the machine was not able to process the original curated dataset of 50 images. To accomodate, this was narrowed down to 25 selected images and the size has been cropped to 140x140. Doing this has not really compromised the data by much as using patterns meant that the cropped versions still very much depicted the original print. In fact, it was better than resizing as it made for a cleaner input.



Although markov models are known for predicting future state based on current state, this project experiments with a higher order markov chain by changing the parameters of the 'n' state. Increasing and decreasing the value of 'n' changes the amount of history the model takes into account when predicting the next step of a sequence.

There are 3 main sets of data used as input. Firstly, the full dataset of 25 images were passed as input after being cropped as mentioned. The second and third are single floral patterns, dissected into multiple pieces. The results from the first set are as follows.

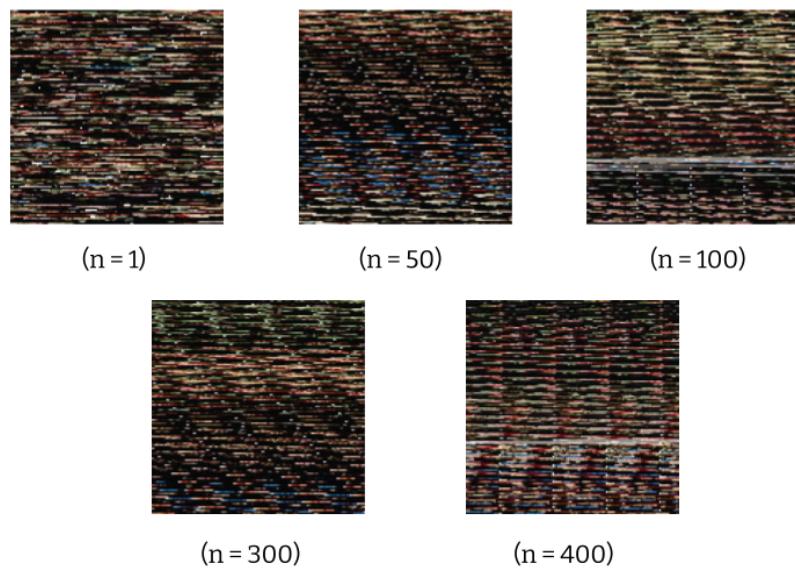
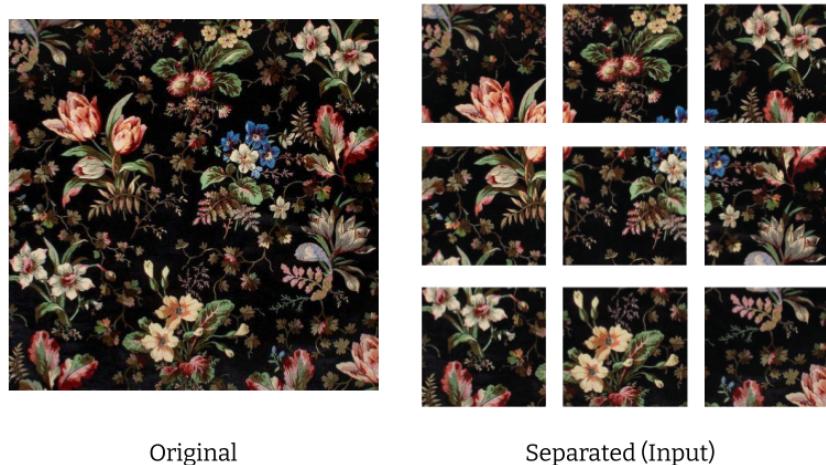


It can be seen that as the ‘n’ order increased, the shapes of the flowers were slightly clearer. Overall, it was quite successful in imitating the prints in that it is visually apparent which image the output is based on.

This can be seen in the example below. Here, the image output size was changed to 240x240 instead of the original set 128x128, creating a collage of several inputs stacked on top of one another.



The second set of images uses one floral print and splits them into 9 pieces, like a jigsaw. Although from the same image, the separated pieces have less of a consistent pattern.



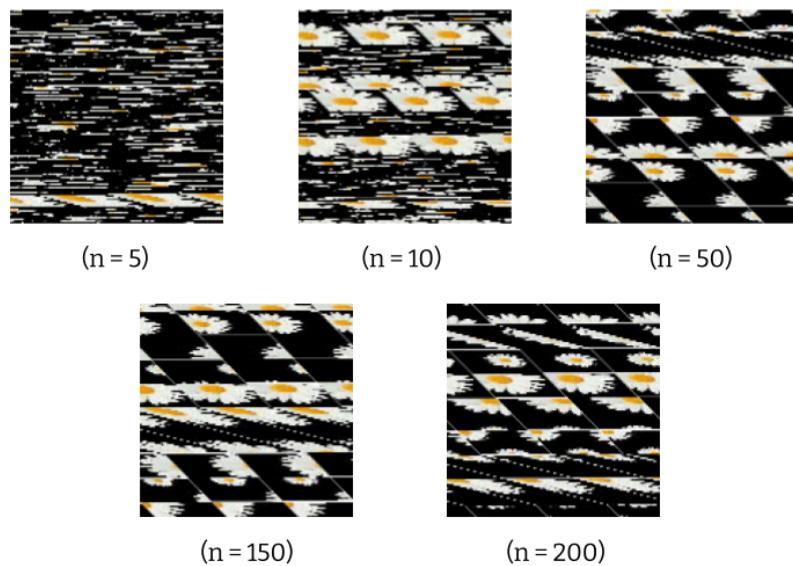
As the order increases 300 and above, the image seems to take on a block pattern. This is in contrast to the $n=1$ result that is more random. With this, the colour palette has successfully been copied. However, the outputs are quite messy visually.

The last set of images also follows this jigsaw approach, except it uses a print with a more consistent pattern and splits it into 30 pieces.



Original

Separated (Input)



(n = 5)

(n = 10)

(n = 50)

(n = 150)

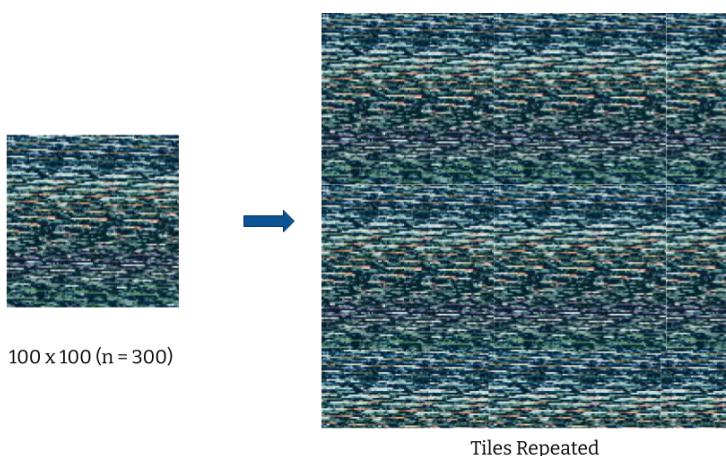
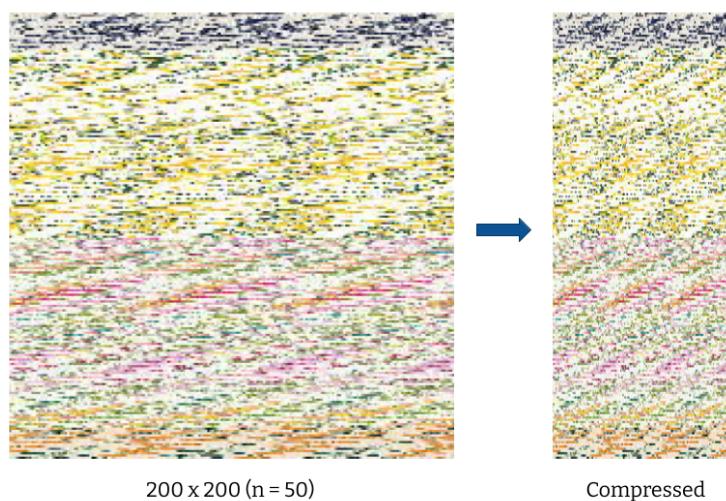
(n = 200)

With this, the goal was to see how well the model was able to put the pieces back together. It is interesting to see how much clearer the results are for this set of images in contrast to the second set.

Although the shape and colour of the daisies have been reproduced a lot more successfully, it does not recognise which parts of the flower match with each other. However, with both sets two and three, it is interesting to see the textures created using low level 'n' values.

Reflection

Traditionally, print design is influenced by trend research. This can be in the form of paid subscription services who gather images from runways and streetstyle, then compile them into reports and moodboards. Textile designers take this as inspiration to create new designs. Having an automated model can help this process.



With the examples above, outputs from the first set of data were experimented with to show possibilities for future use. As seen below, changing the image size makes a significant difference. On its own, the results are not always usable. However, by training a model on current trends, it can produce starting points of inspiration to be modified for artistic or commercial use.