

**Generating HP Mosaic seeds
using generative adversarial network**

Original seed pattern



Cropping area



Rotation



Scaling



- HP Mosaic let you create automatic designs based on core patterns. It automatically generates a potentially unlimited number of unique graphic designs based on a fixed number of base patterns
- The heart of HP Mosaic are one or few base patterns which are vector-based graphics (SVG or PDF format). The graphics are varied by rotation, scaling and color change to always create new patterns





HP Mosaic campaigns

▼ Problem description

Creating Mosaic seeds is a hard task. The design requires to be **complex as possible in vector format** and **fits the specific campaign/brand**.

- Time consuming
- Weak design outcome
- Uniqueness

GOAL

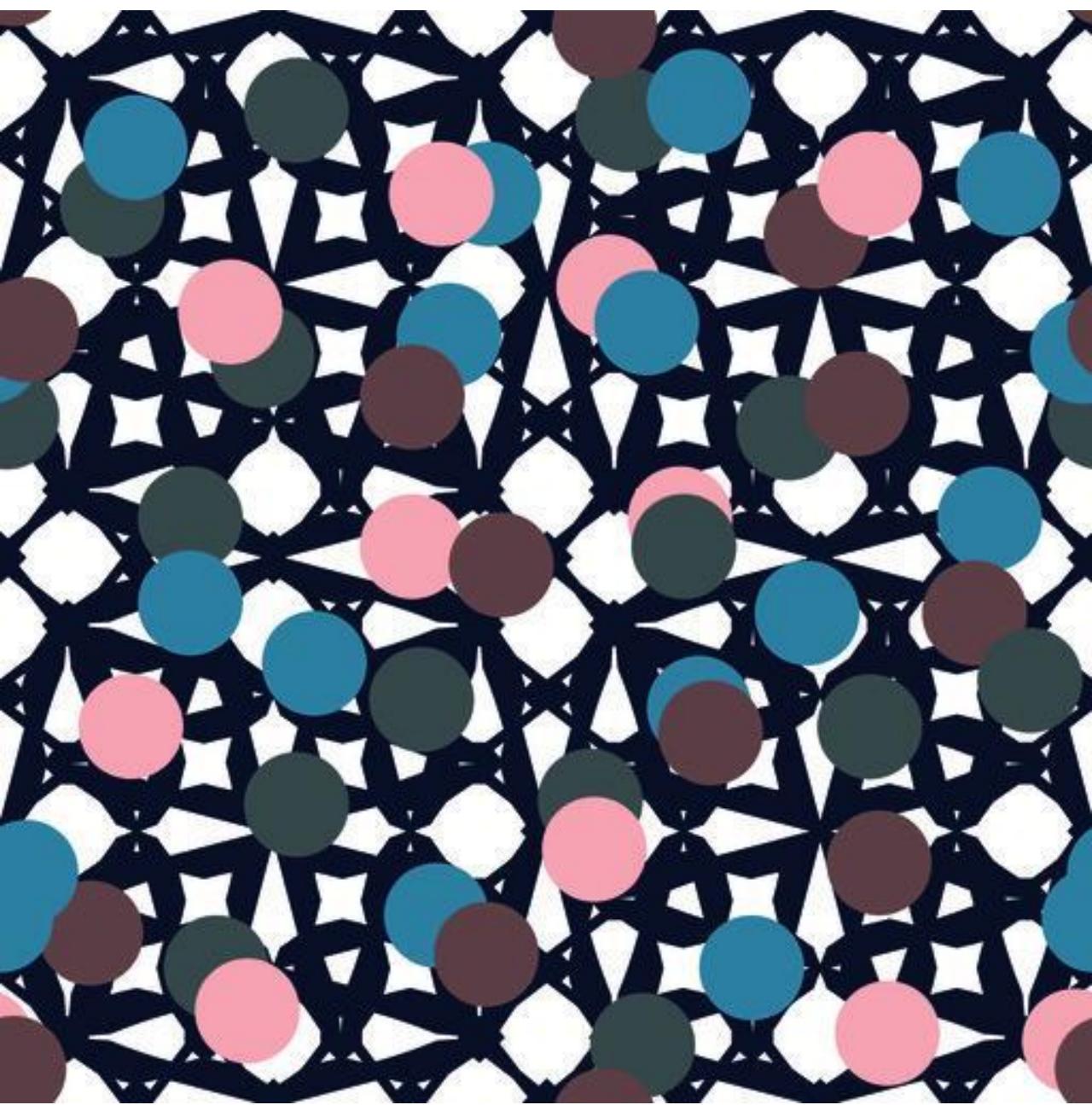
Help the designers to create seeds
for Mosaic algorithm

Proposed solution

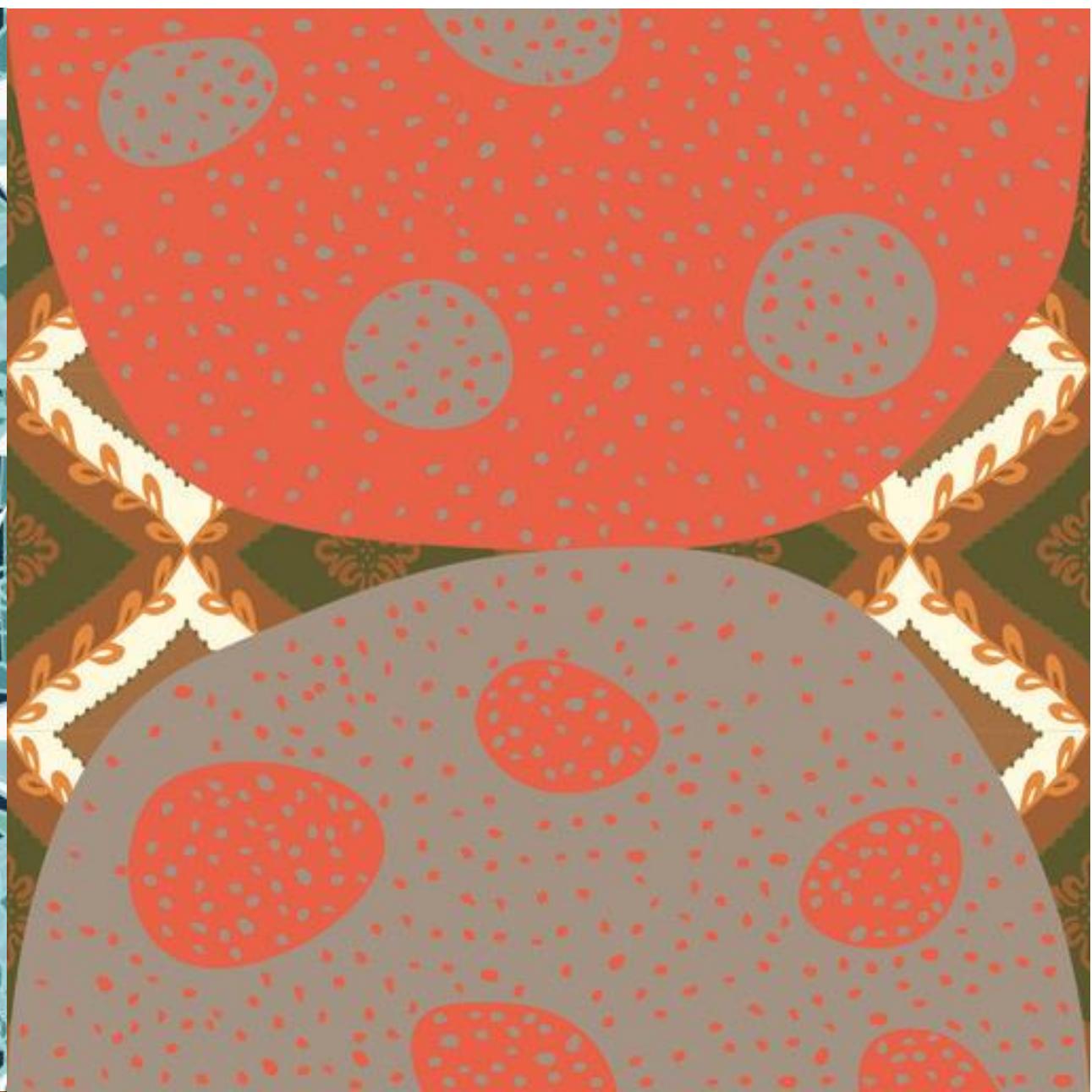
Using Generative adversarial networks (GAN) for creating Mosaic seeds based on a dataset of existing Mosaic seeds

The dataset

- For training the GAN properly and getting a variety of unique designs, we need to use large dataset as possible
- I've managed to collect just 400 mosaic base patterns (seeds) in vector format that fits the HP Mosaic algorithm requirements, which is a very small dataset for training a GAN and achieving suitable results
- In order to increase the dataset size I used data augmentation
- The dataset was augmented with color shuffling and combinations of the vector images
- The 400 dataset images augmented into 4000 images







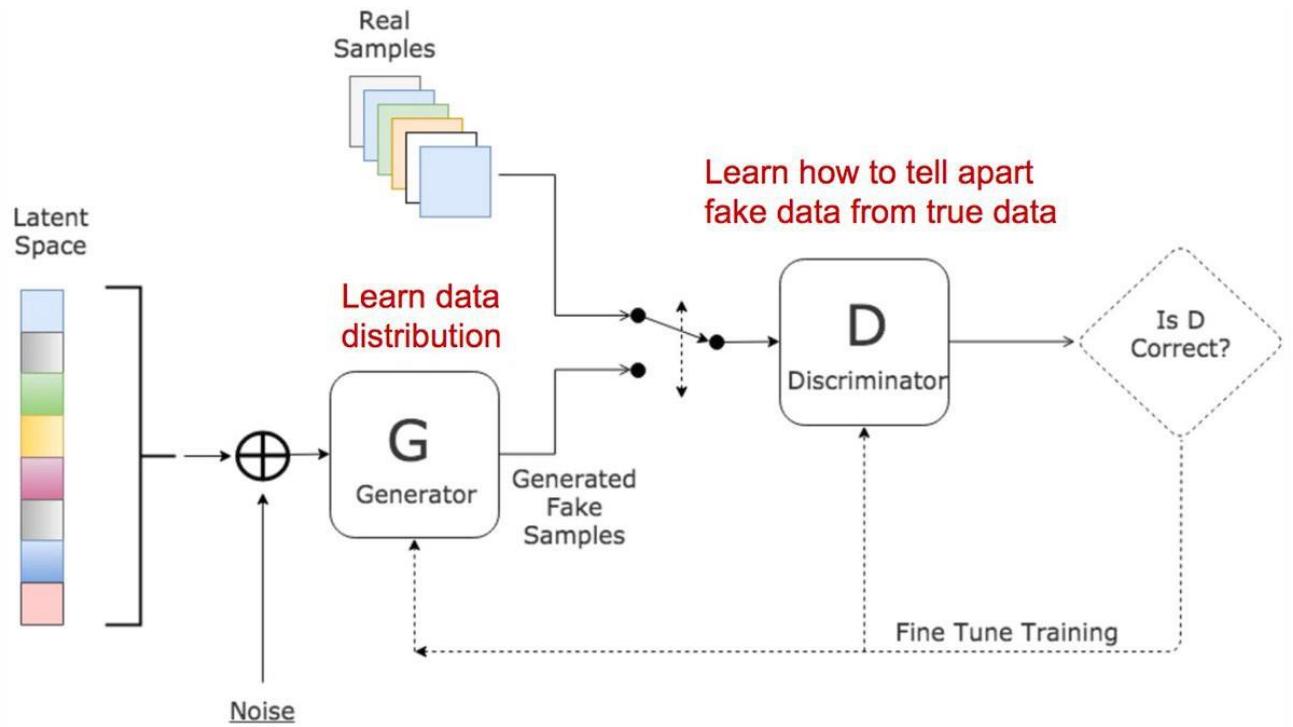
Training Images



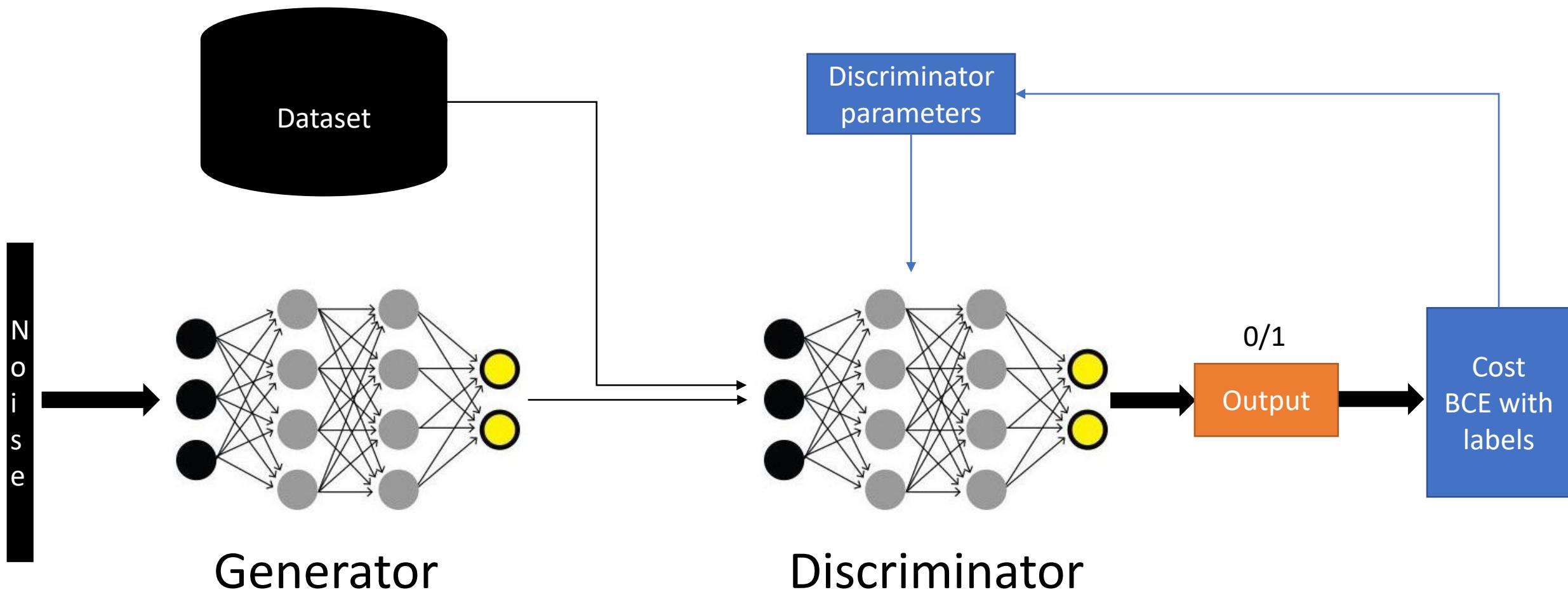
GAN Architecture

A generative adversarial network (GAN) has two parts:

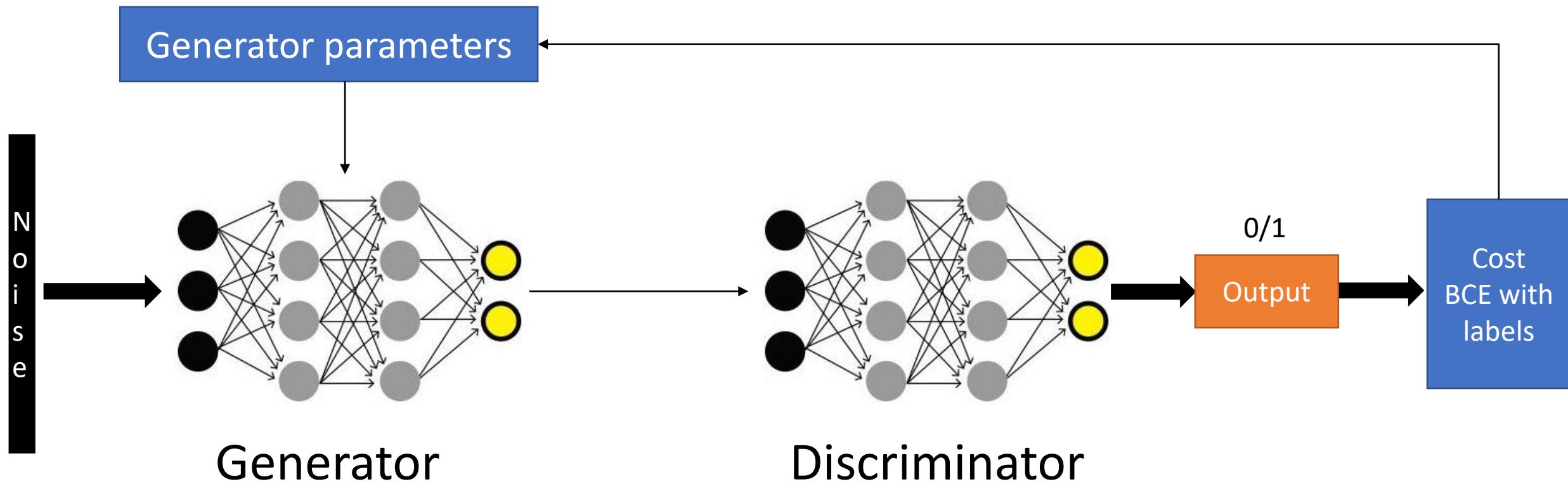
- The **generator** learns to generate plausible data. The generated instances become negative training examples for the discriminator.
- The **discriminator** learns to distinguish the generator's fake data from real data. The discriminator penalizes the generator for producing implausible results.



Discriminator weights update



Generator weights update



Loss function – Binary cross entropy

$$BCE = -\frac{1}{N} \sum_{i=0}^N [y_i \cdot \log(\hat{y}_i) + (1 - y_i) \cdot \log(1 - \hat{y}_i)]$$

| Y_i | \hat{Y}_i | $Y_i \log(\hat{Y}_i)$ |
|-------|-------------|-----------------------|
| 0 | any | 0 |
| 1 | 0.99 | ~0 |
| 1 | ~0 | ~-inf |

| Y_i | \hat{Y}_i | $(1 - Y_i) \log(1 - \hat{Y}_i)$ |
|-------|-------------|---------------------------------|
| 1 | any | 0 |
| 0 | 0.01 | ~0 |
| 0 | ~1 | ~-inf |

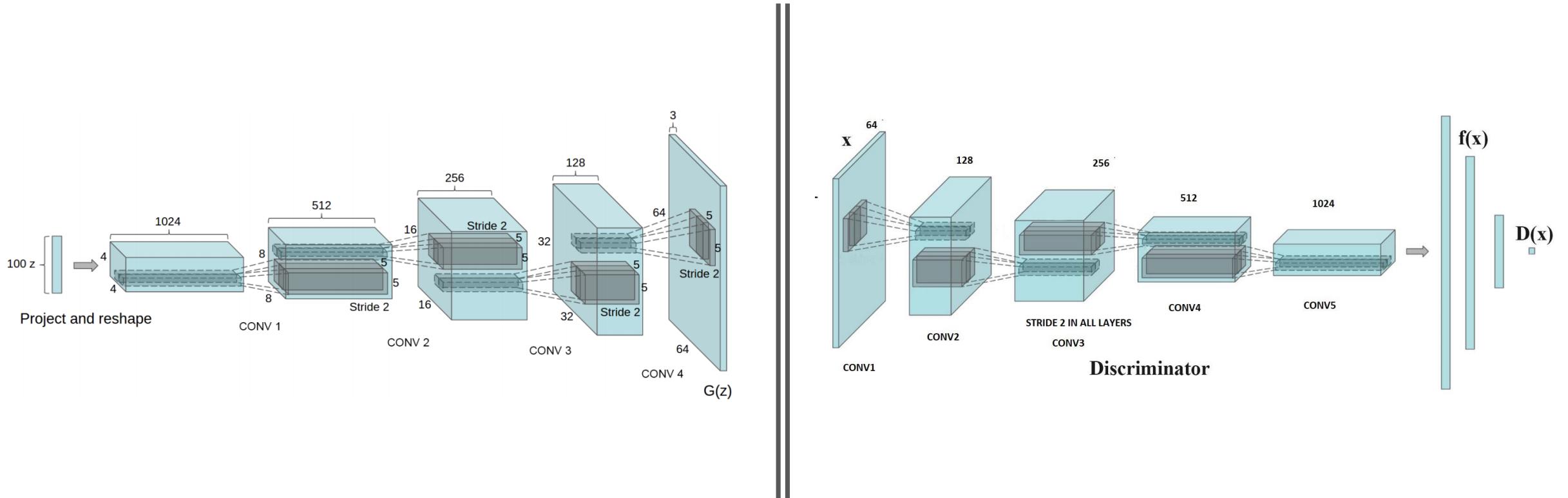


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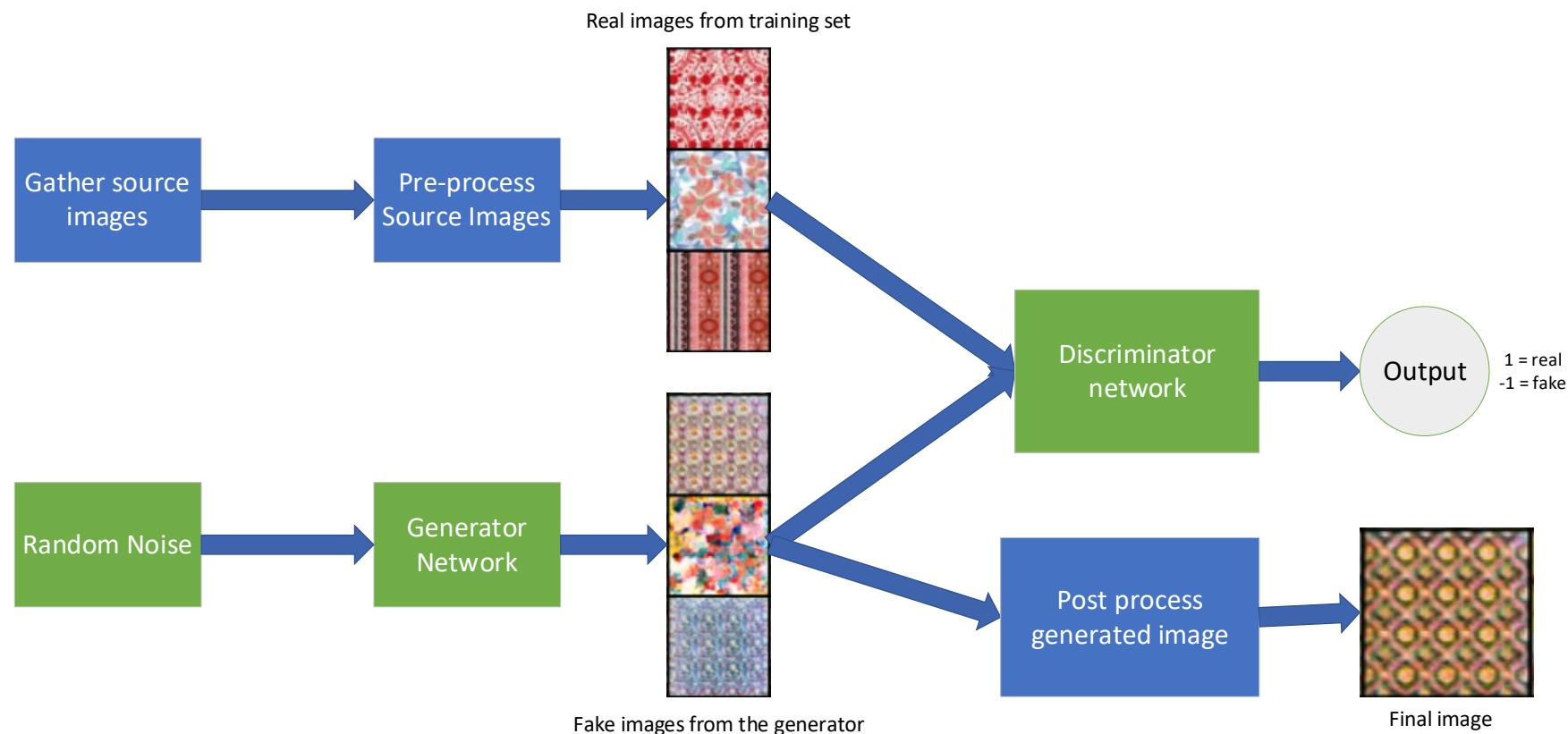
GAN common problems

- Vanishing Gradients
- Mode Collapse
- Failure to Converge

DCGAN



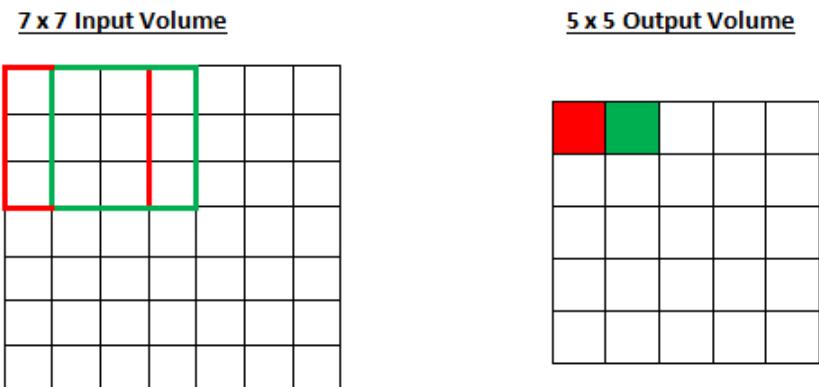
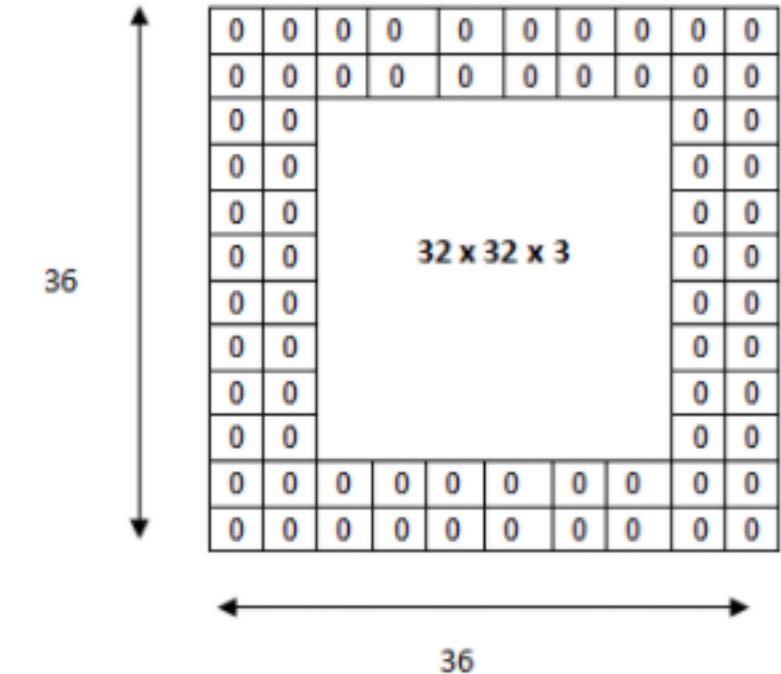
Training process



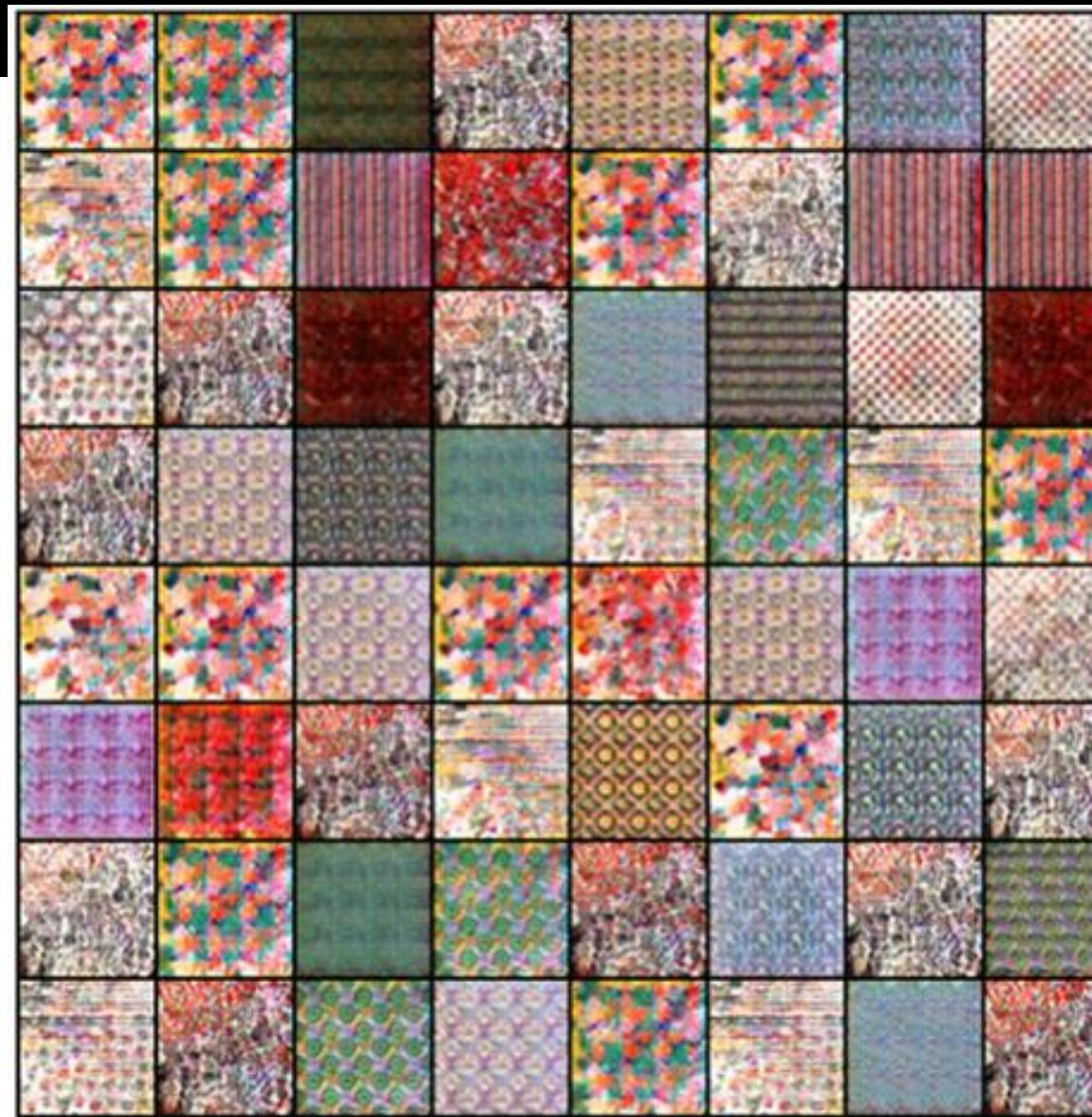
Experiments with DCGAN



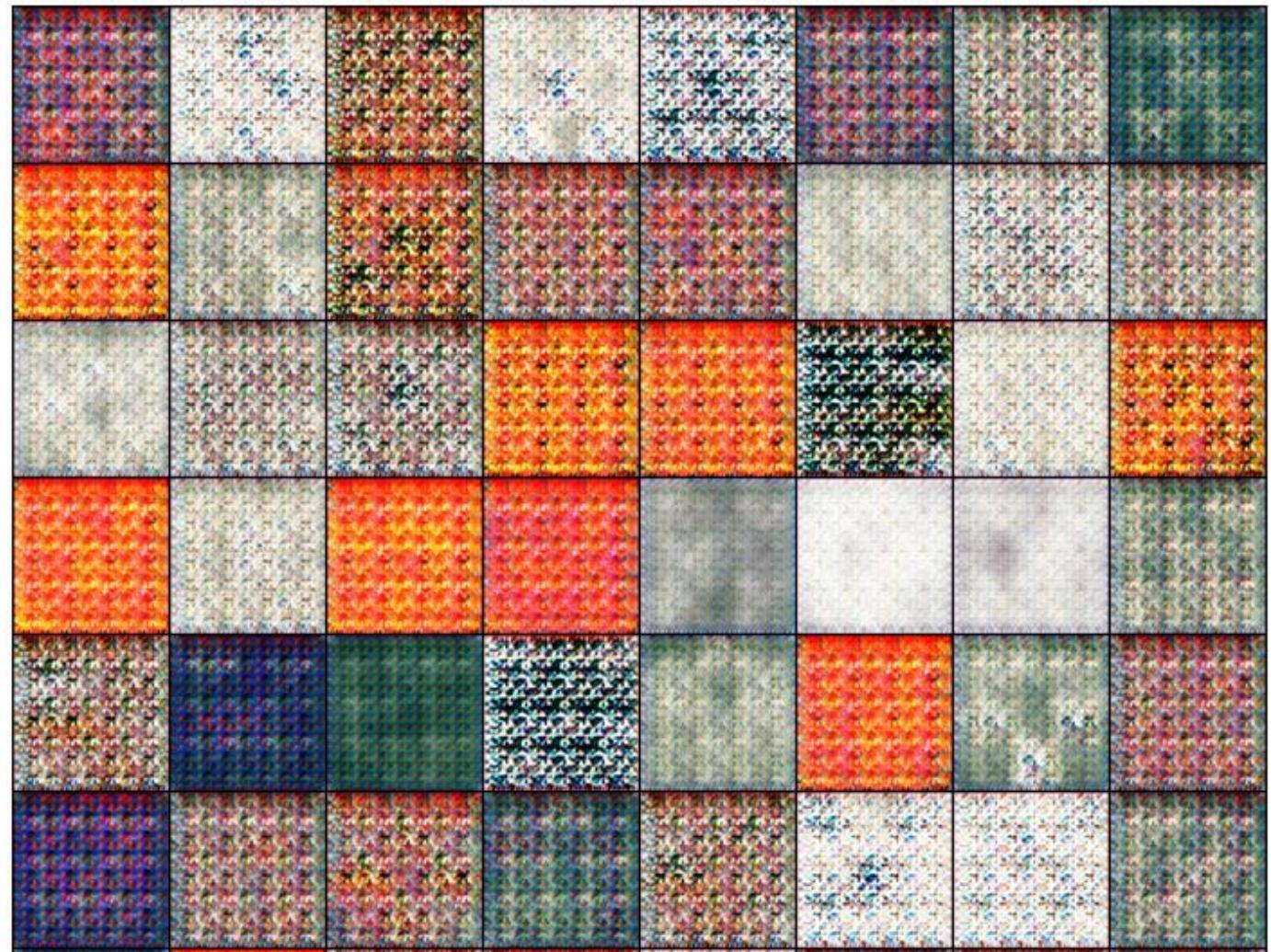
- Kernel size
- Padding
- Stride
- Number of features
- Adding and changing layers



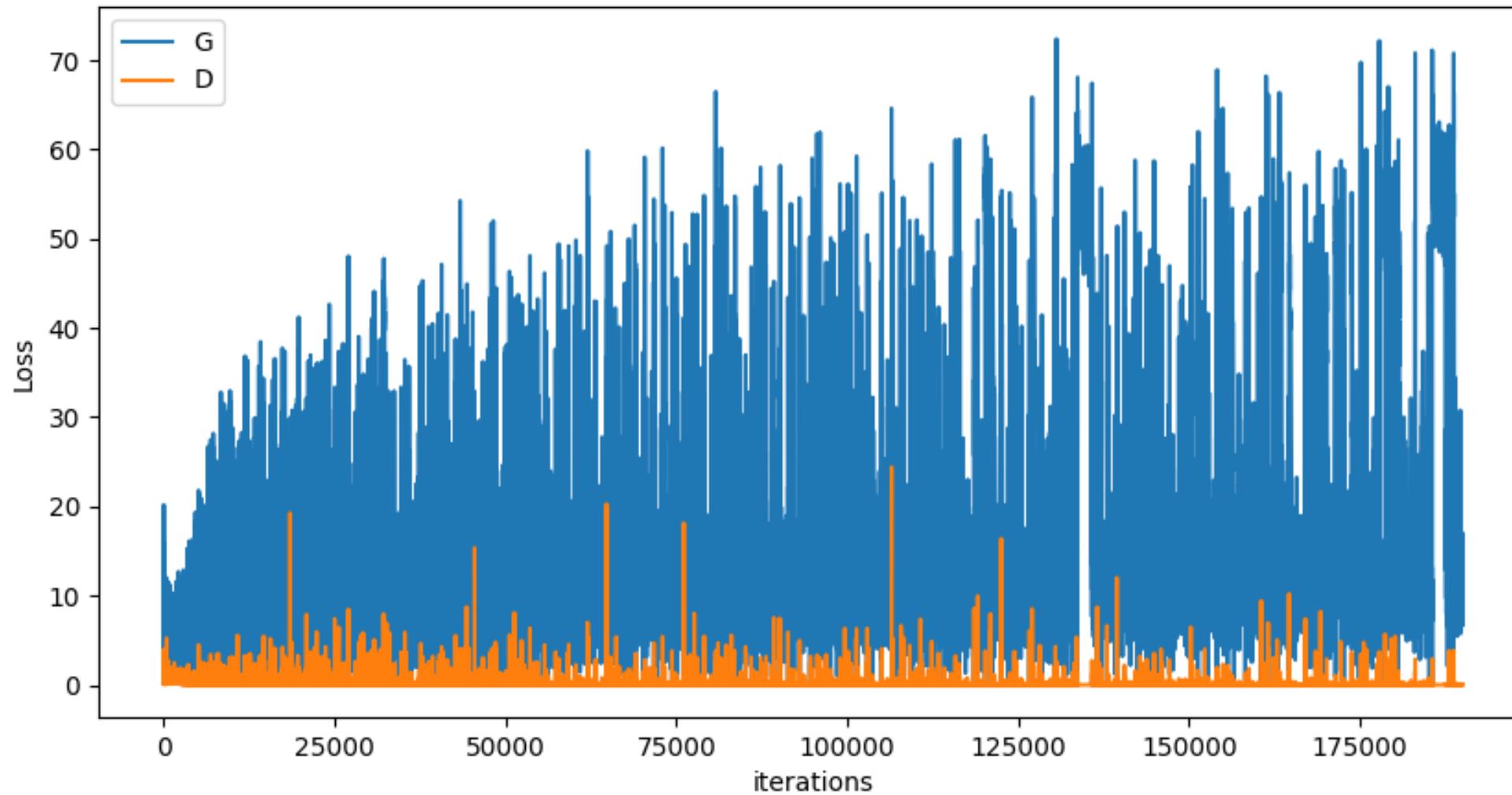
DCGAN Results



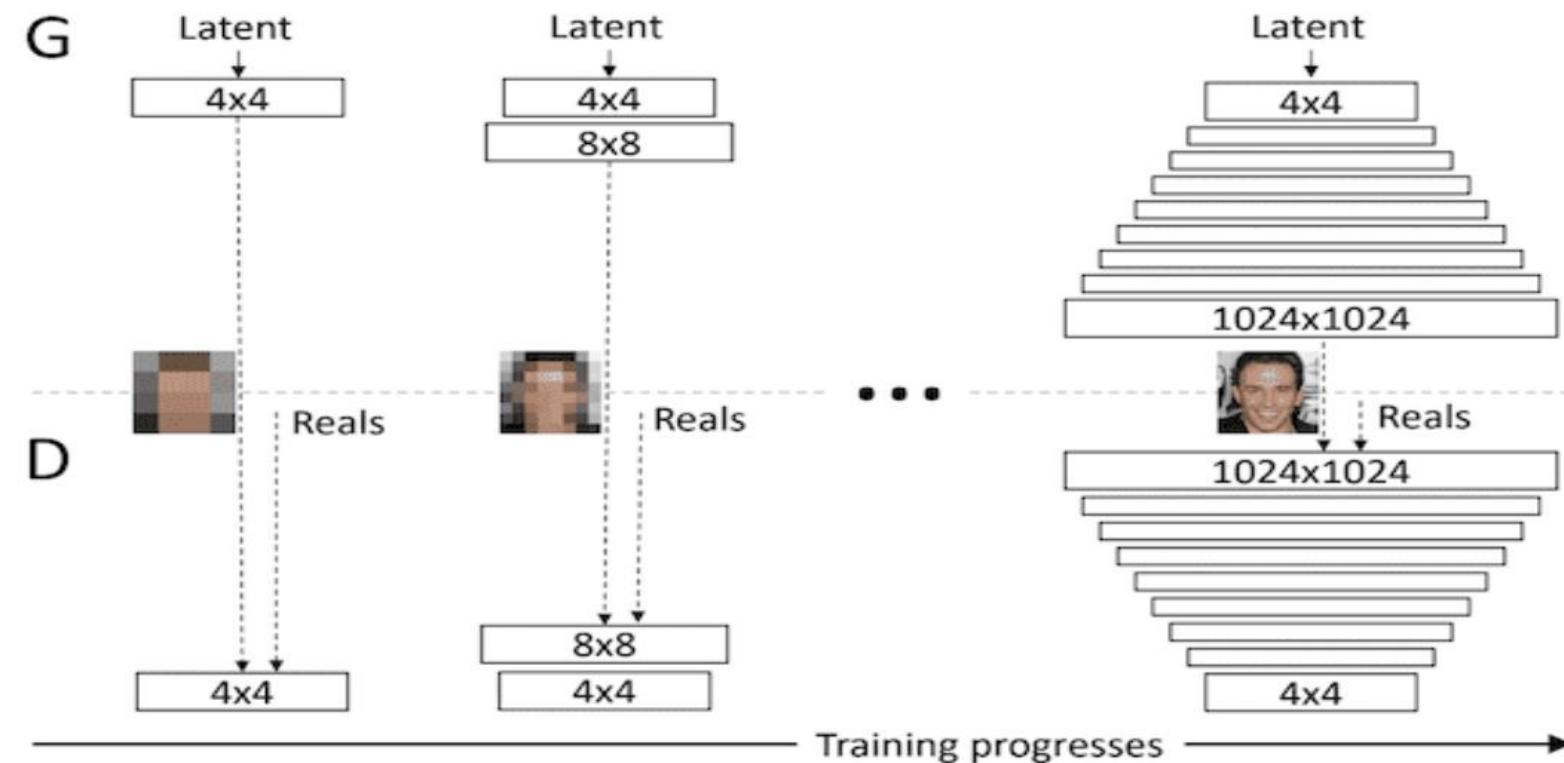
Attempt to generate larger
images using more layers



Generator and Discriminator Loss During Training

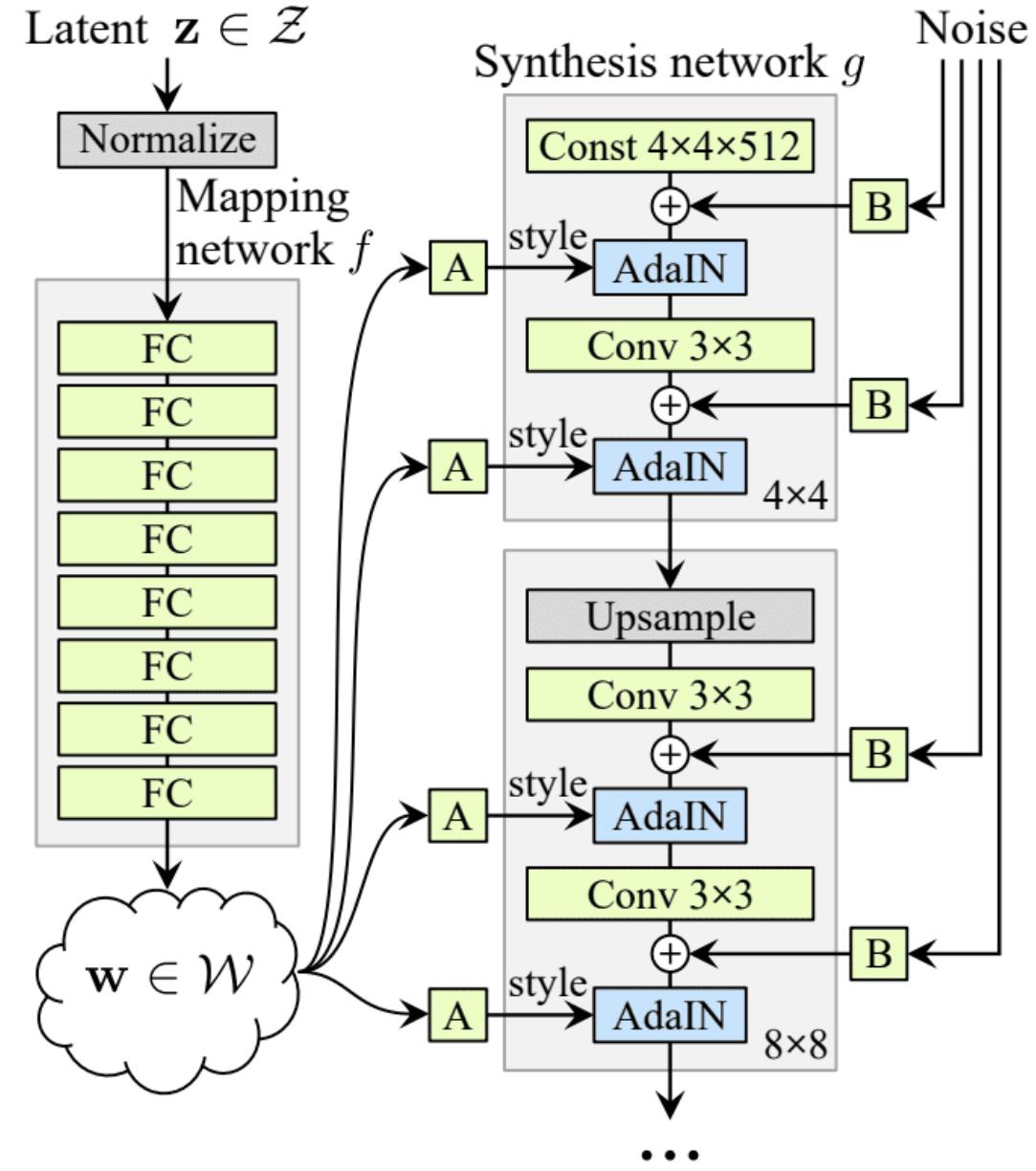


ProgressiveGAN



StyleGan

- Baseline Progressive GAN.
- bilinear upsampling.
- mapping network and adaptive instance normalization
- Removal of latent vector input to generator.
- noise to each block.



Testing process

- The images are fed into the Discriminator Network as the “real” images. A set of 512 random numbers are chosen and fed into the Style Mapper and Generator Networks to create the “fake” images. The result is fed back into the three networks to train them.
- After training the networks for 128 epochs with batches of 64, the generator output those results

StyleGAN with Adaptive Discriminator Augmentation

One of the major improvements in StyleGAN ADA is dynamically changing the amount of image augmentation during training.

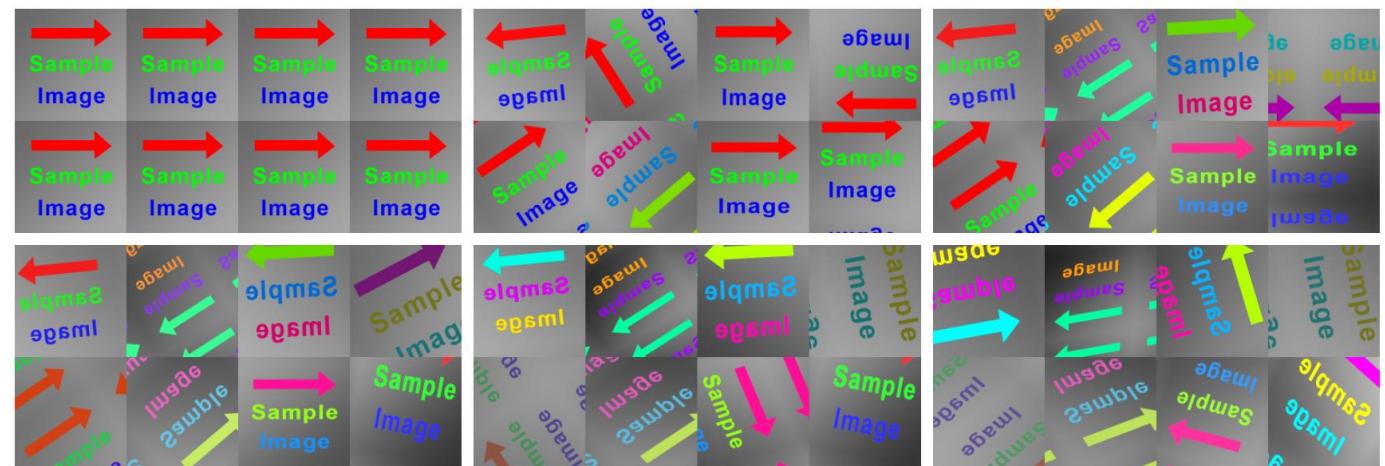
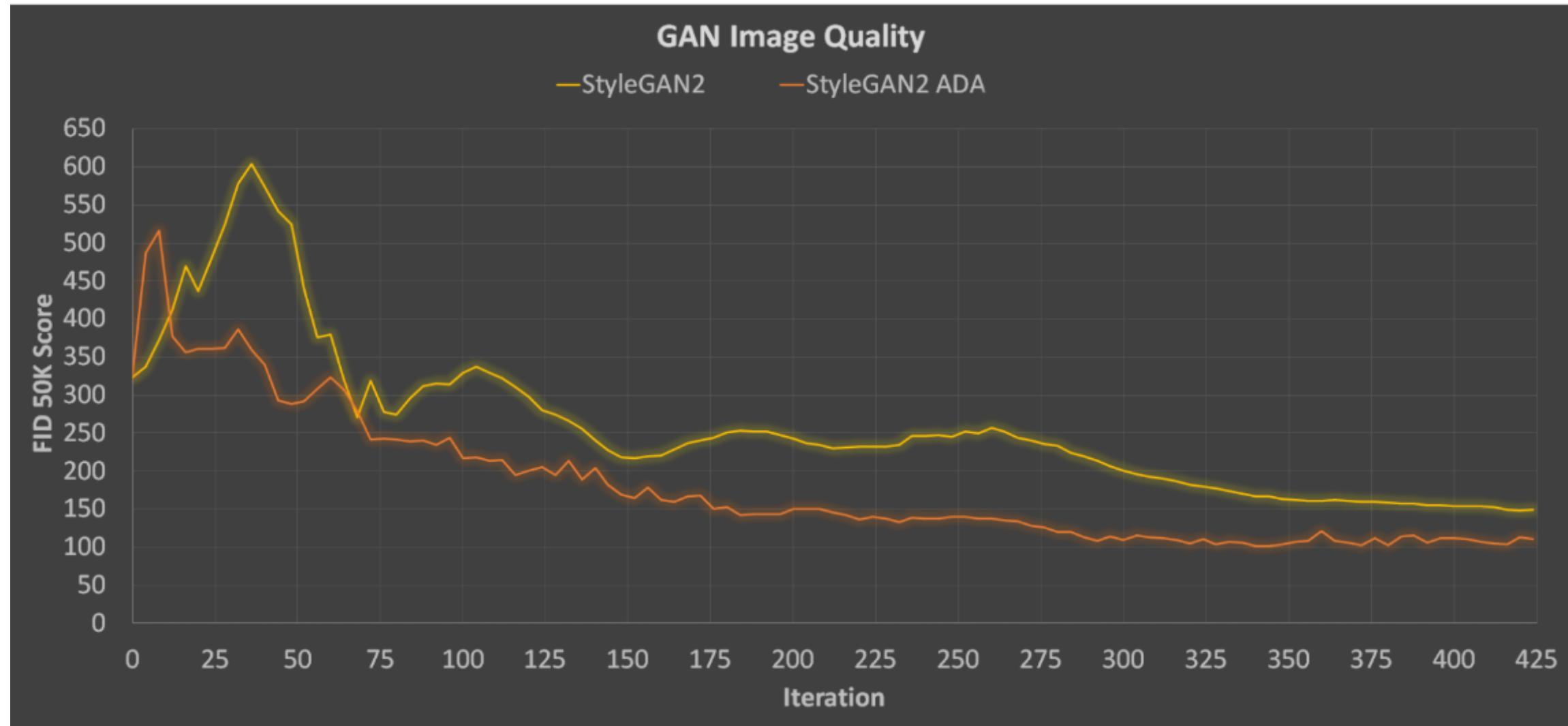


Image Augmentation with (top) $p=0.0, 0.2, 0.4$ (bottom) $p=0.6, 0.8, 1.0$, Images by Author



Training StyleGAN with Adaptive Discriminator Augmentation

- After training the networks with the same settings as before (128 epochs with batches of 64), the generator output the following images

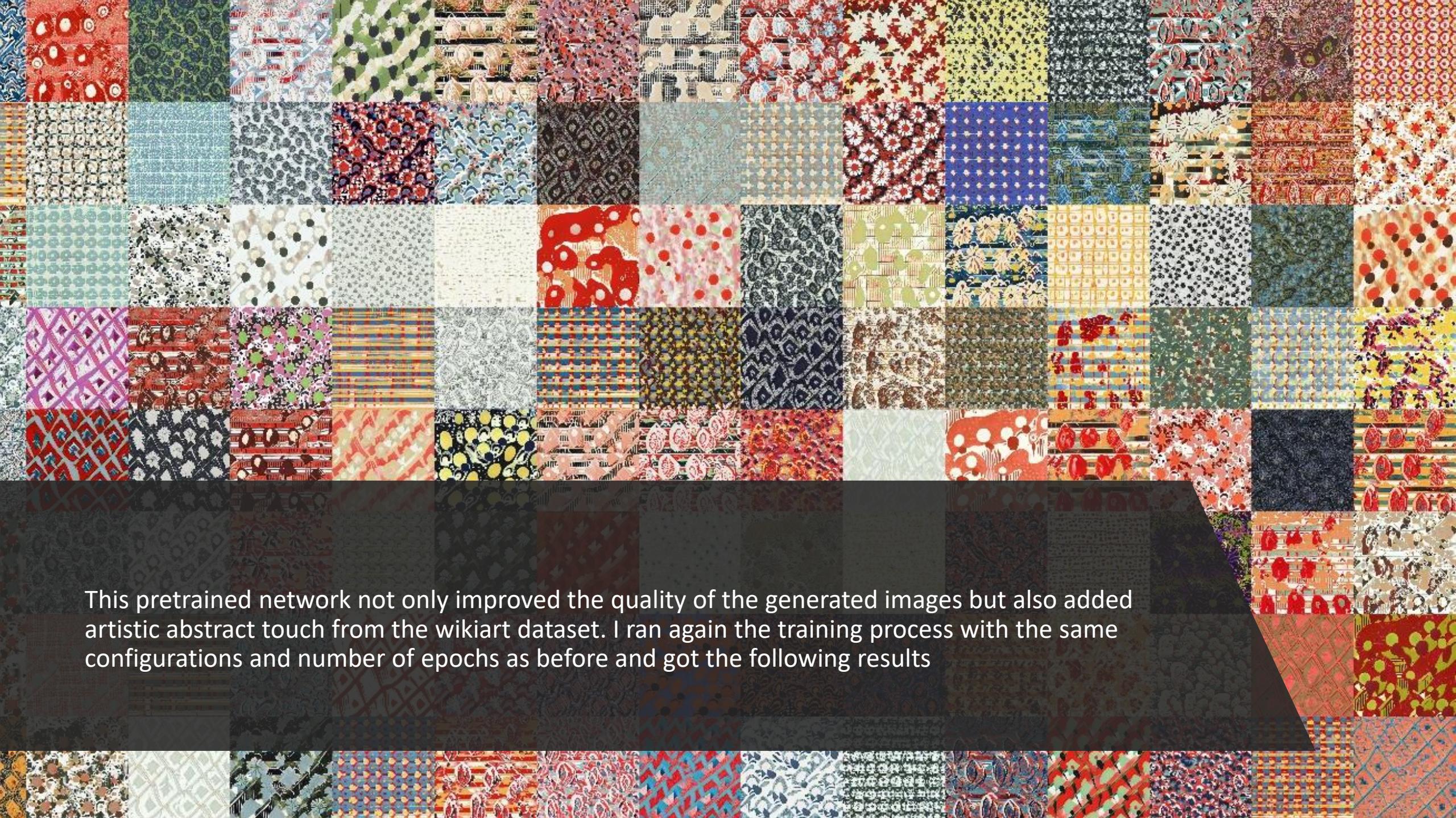


Transfer Learning

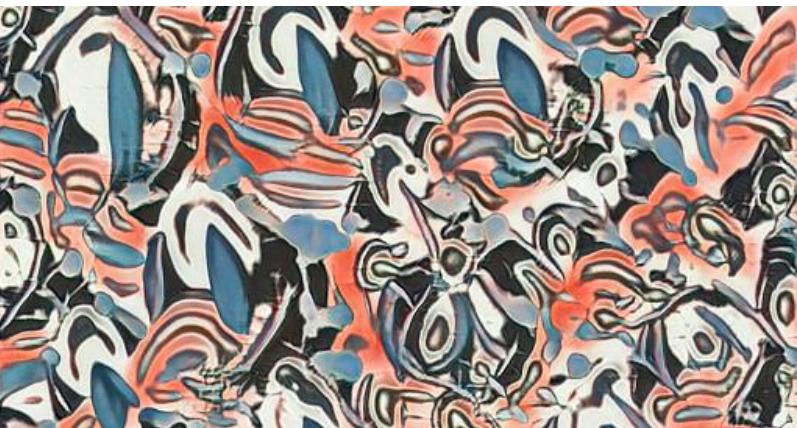
- It's possible to improve the quality of the generated images by first training the GAN on a different, larger set of images, and then further train the model using the smaller dataset. This technique is called Transfer Learning. It was first described as a technique for training NNs in 1976.
- *"Transfer Learning is technique that uses a pre-trained neural network trained for Task 1 for achieving shorter training time in learning Task 2. — Stevo Bozinovski"*
- I found a pre-trained GAN network on a public domain from Wikiart, and I used it as my that had been trained with tens of thousands of artistic photos training starting point.



Samples from the art works used for the Wikiart pretrained network



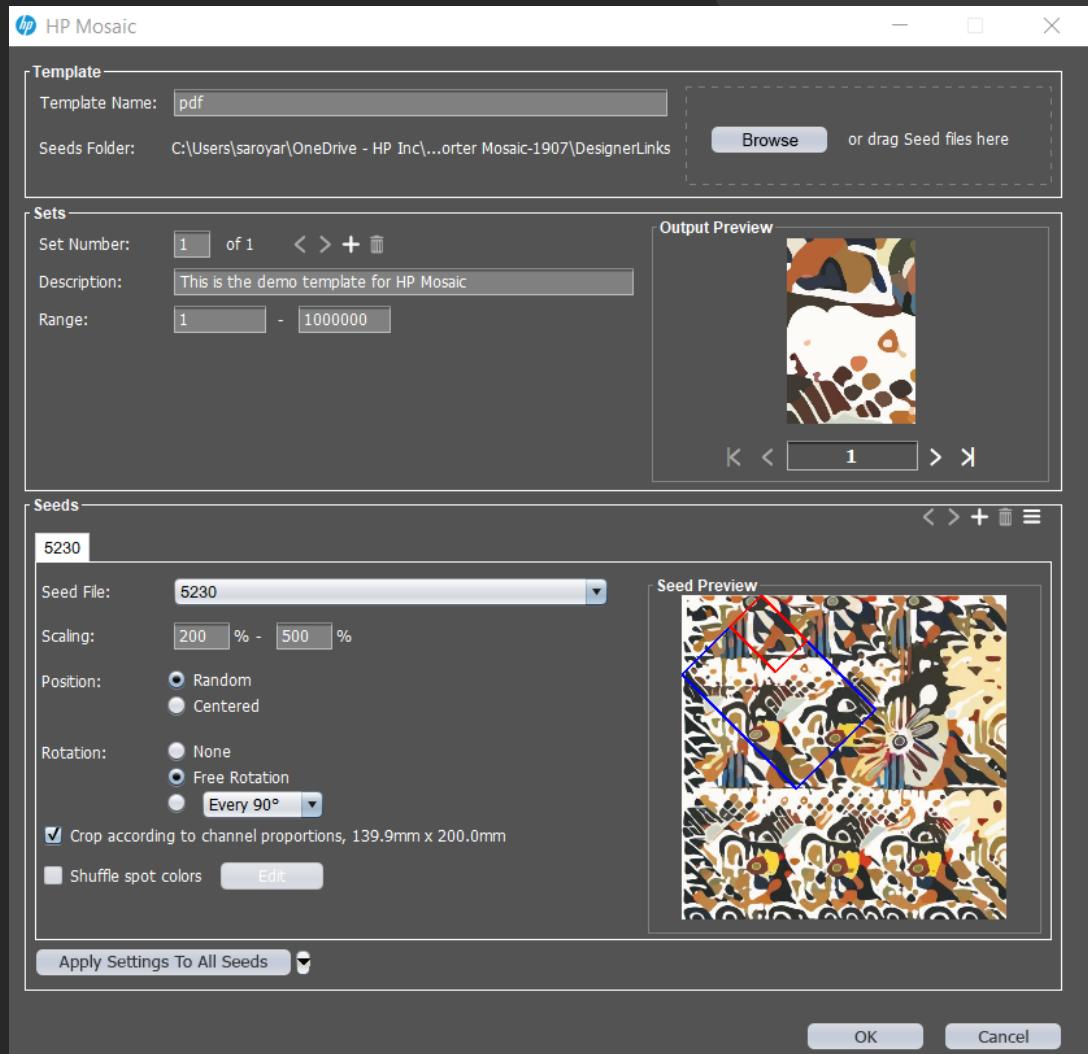
This pretrained network not only improved the quality of the generated images but also added artistic abstract touch from the wikiart dataset. I ran again the training process with the same configurations and number of epochs as before and got the following results



Large samples

Mosaic algorithm with the generated seeds

The following image is HP Mosaic plugin for Adobe Illustrator, I selected the first sample seed from above and configured free rotation, random position and scaling from 200%-500%.



The output
of the
algorithm
with custom
template



PrintOS

Composer > Templates > Template

Current records quota: 99% Details... Templates > Template

Volkswagen Transporter Mosaic-1907

VDP Template Volkswagen Transporter Mosaic-1907

Description

Number Of Pages 1

Preset Default Preset

Mode Fast

Imposition Template 6up

External asset library

Drag CSV, TXT file or click to choose one

Preview Record

3

Record Number out of 100

Skip First Record

yala
3

APPLY CHANGES COMPOSE

PREVIEW WITH IMPOSITION

Page Preview

Page Number out of 1

PrintOS

Composer > Templates > Template

Current records quota: 99% Details... Templates > Template

Volkswagen Transporter Mosaic-1907

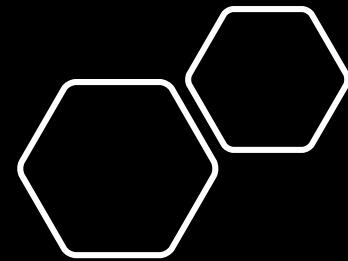
Mosaic channel 1 Mosaic channel 2

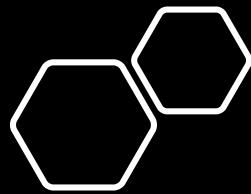
APPLY CHANGES COMPOSE

PREVIEW WITH IMPOSITION

Page Preview

Page Number out of 1





Projecting

- The StyleGAN generator model is basically a network of weights, we can try to represent an input image with those weights (projecting an input image into the latent space of the model). We can use this projection to combine the style of an input image with a given seed by learning the input image.

