ProGAN
StyleGAN
StyleGAN2
StylegGAN2-ADA

(NVIDIA)

slides shamelessly and mindlessly stolen from

https://towardsdatascience.com/progan-how-nvidia-generated-images-of-unprecedented-quality-51c98ec2cbd2,

https://towardsdatascience.com/explained-a-style-based-generator-architecture-for-gans-generating-and-tuning-realistic-6cb2be0f431,

https://towardsdatascience.com/stylegan2-ace6d3da405d,

and the original papers
https://arxiv.org/abs/1710.10196
https://arxiv.org/abs/1812.04948
https://arxiv.org/abs/1912.04958
https://arxiv.org/abs/2006.06676

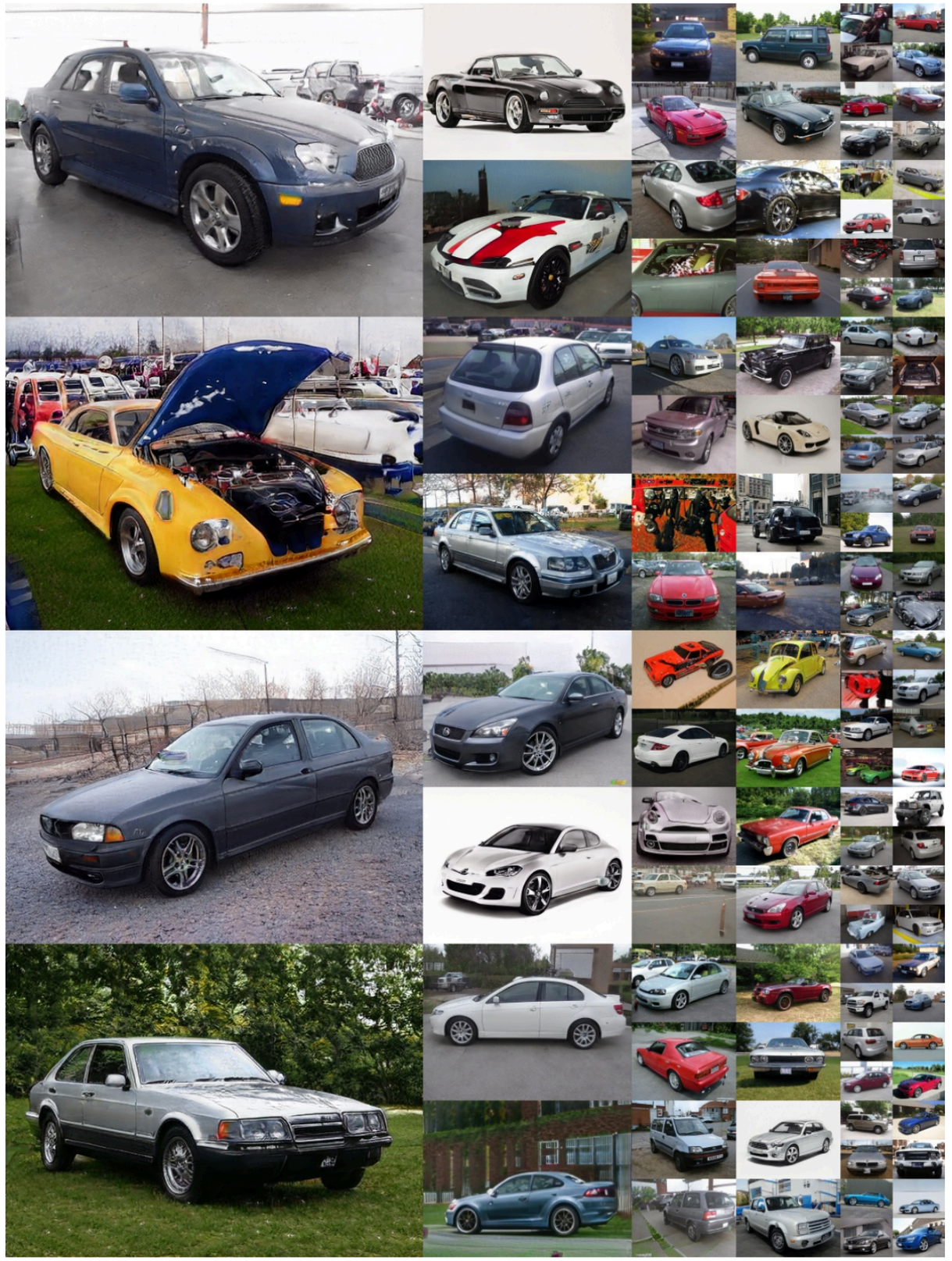
Why StyleGAN in particular?

- The talk presents a dozen or so engineering tricks employed by the creators of the very successful generative model StyleGAN (Karras et al, NVIDIA).

- In themselves, probably not too many of these tricks would deserve extra attention from us when looking at the broader picture of deep learning methods.

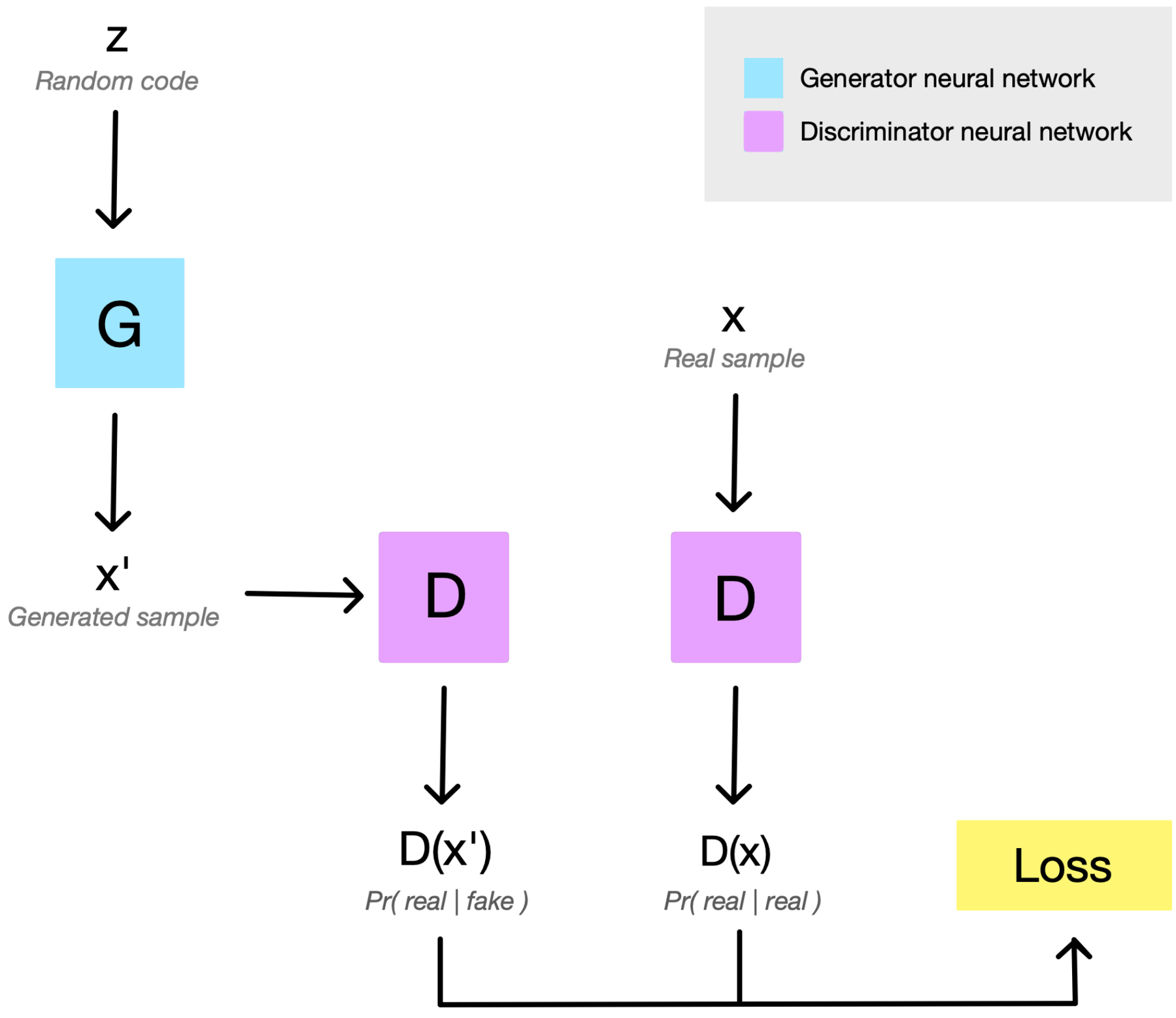
- But together they give a diverse cross-section of useful techniques that we can employ when working with image data, and especially when generating image data.

Not just faces

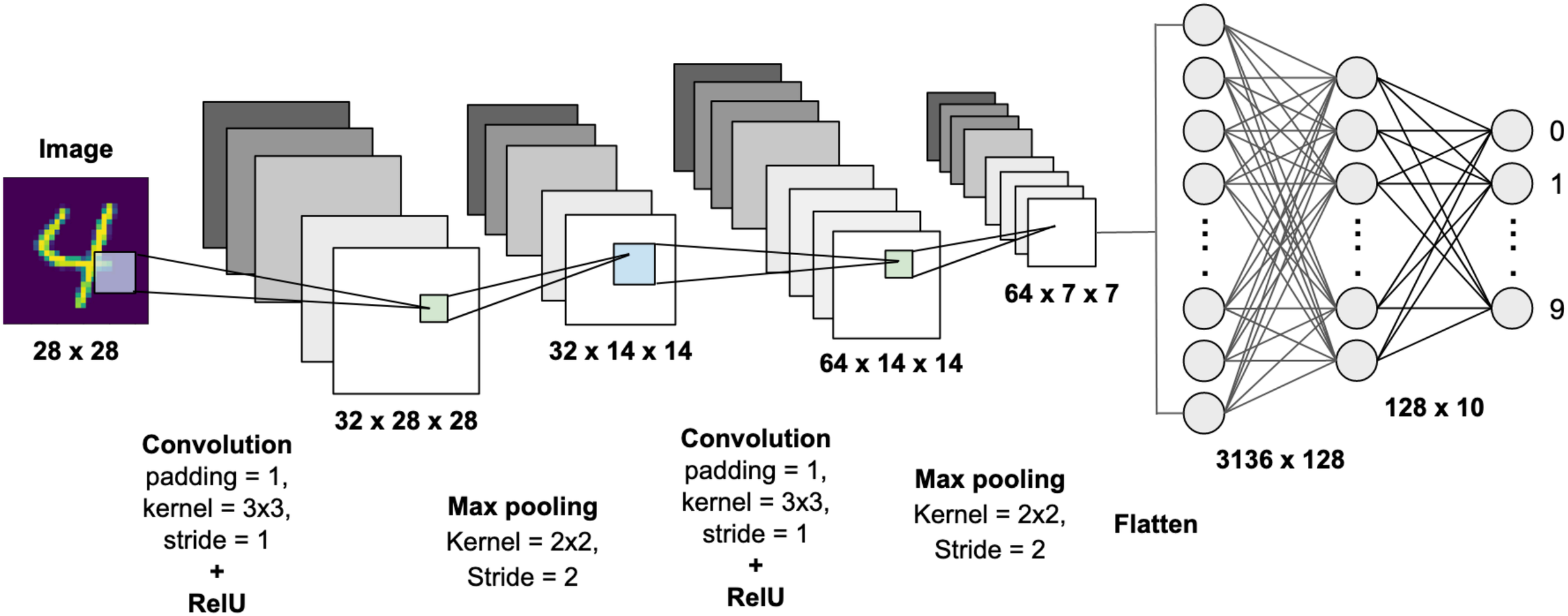


Negative cherry-picking (StyleGAN1)

GAN reminder

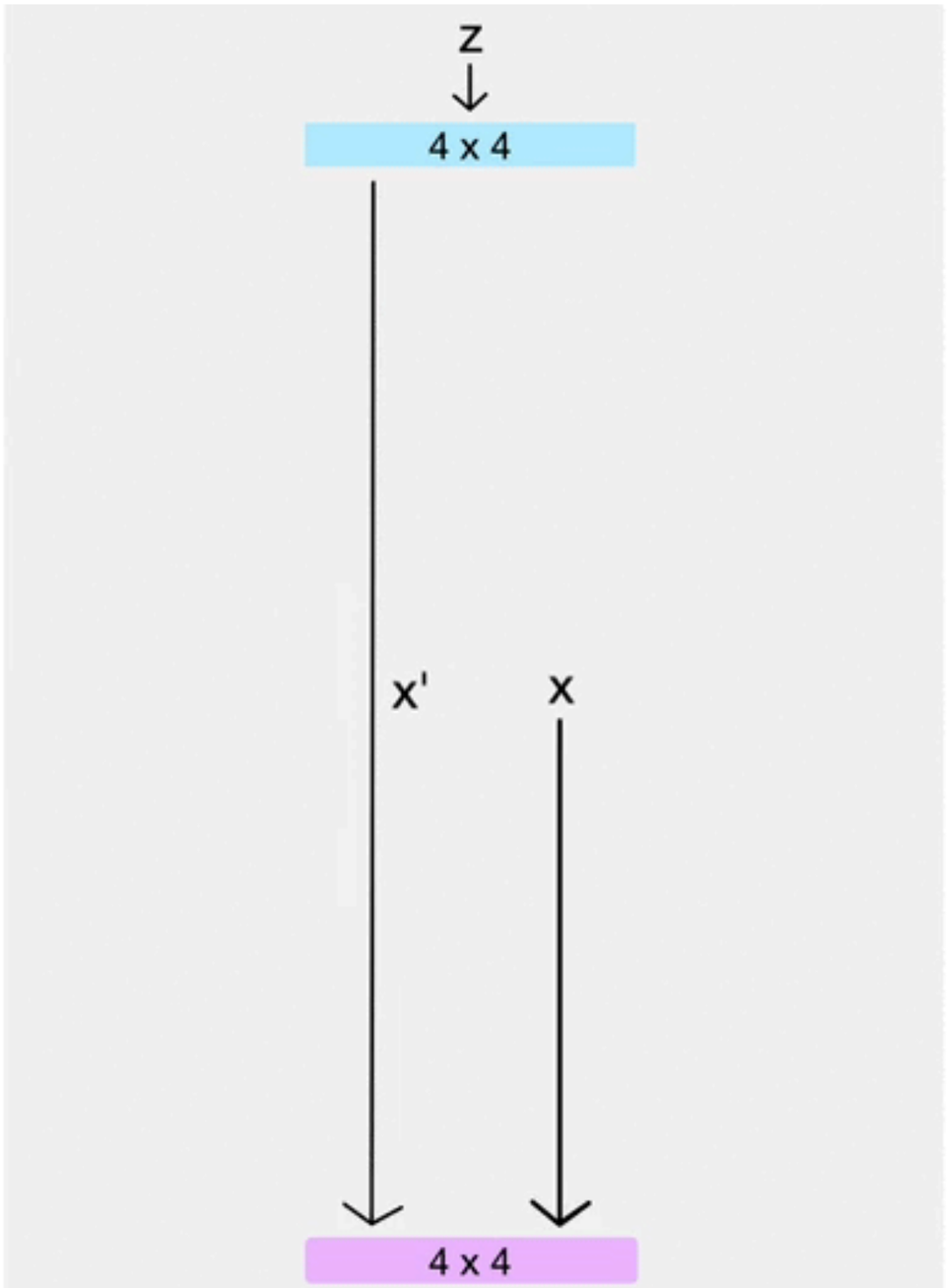


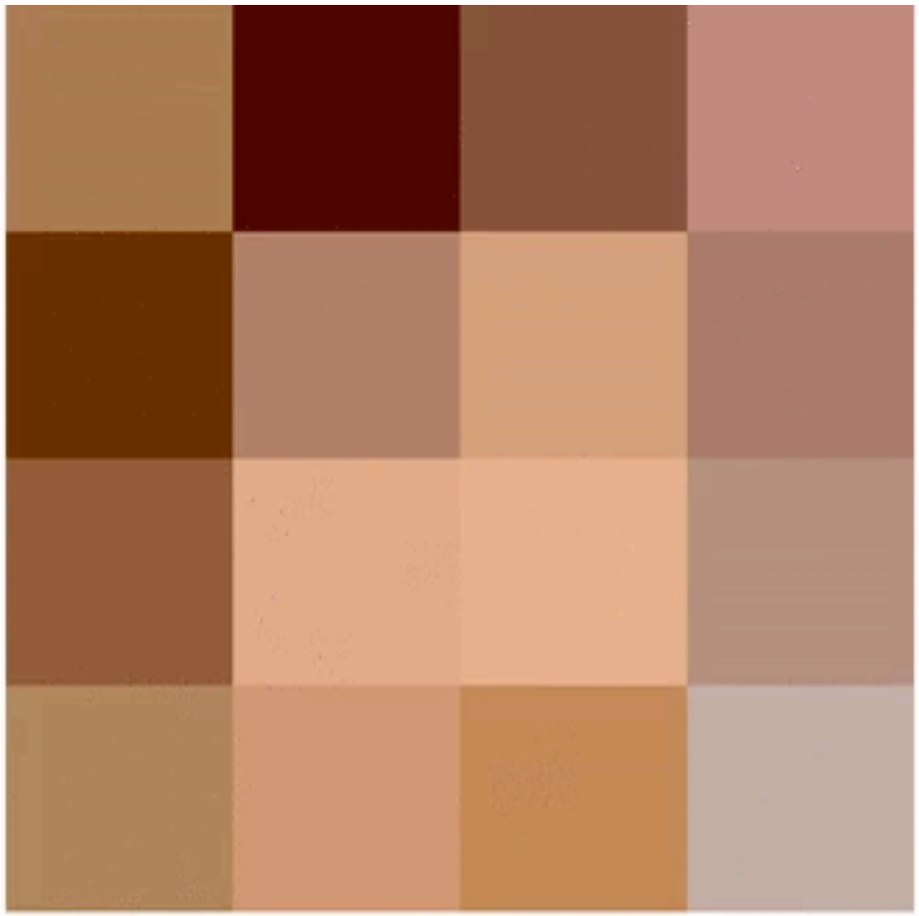
Feature map reminder



This image explains recognition, but feature maps for generators are fundamentally the same: (height x width x channels) sized 3D arrays.

ProGAN (progressive growing of GANs) 2017 November





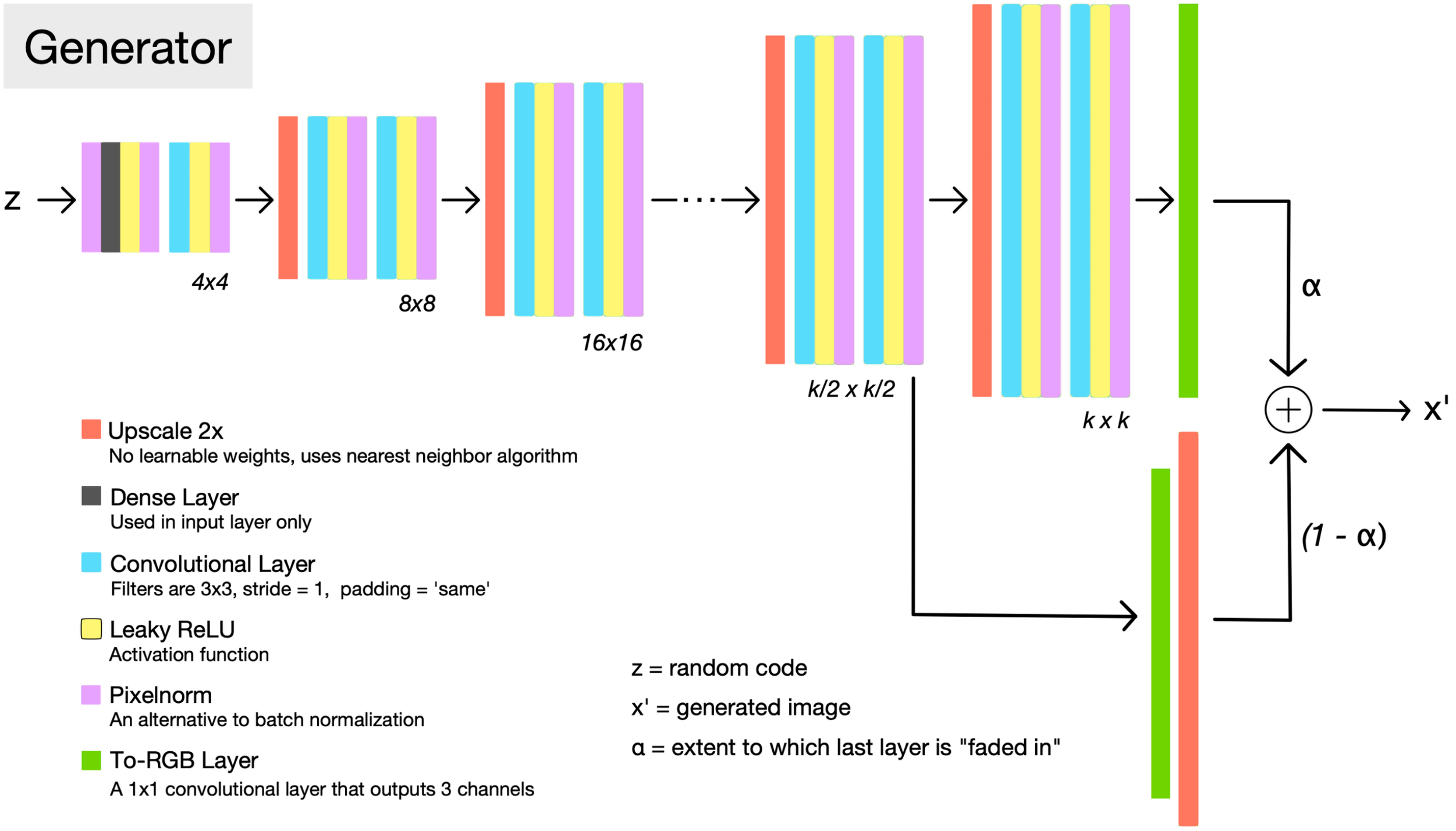
Training time: 0 days
4x4 resolution

Generator
Discriminator

z = random code
x = real image
x' = generated image

The pdf is not animated, see the animation here.

Generator

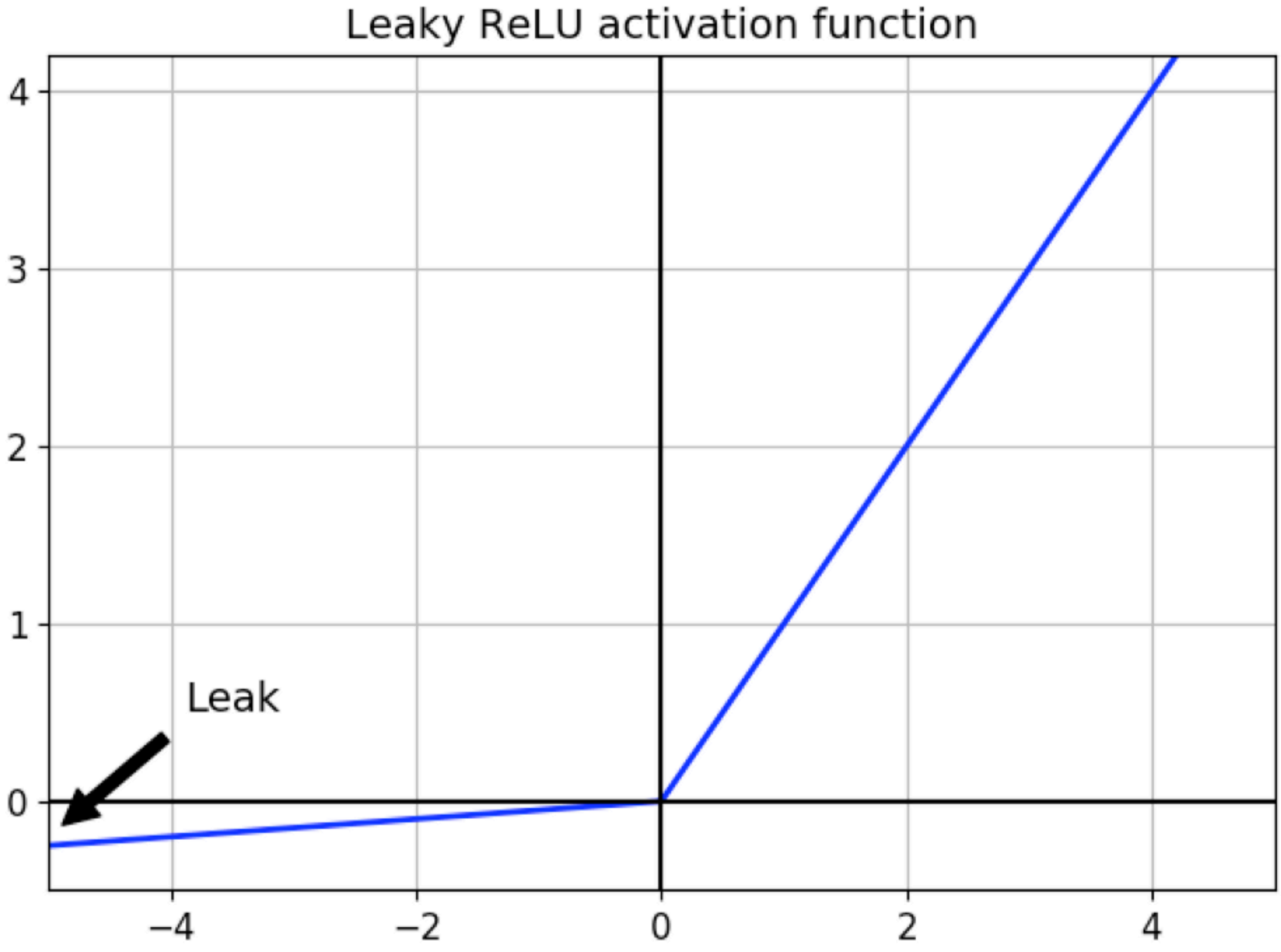


- **Upscale 2x**
  No learnable weights, uses nearest neighbor algorithm
- **Dense Layer**
  Used in input layer only
- **Convolutional Layer**
  Filters are 3x3, stride = 1, padding = 'same'
- **Leaky ReLU**
  Activation function
- **Pixelnorm**
  An alternative to batch normalization
- **To-RGB Layer**
  A 1x1 convolutional layer that outputs 3 channels

z = random code

x' = generated image

α = extent to which last layer is "faded in"


Leaky ReLU activation function
4
3
2
1
0
Leak
−4
−2
0
2
4

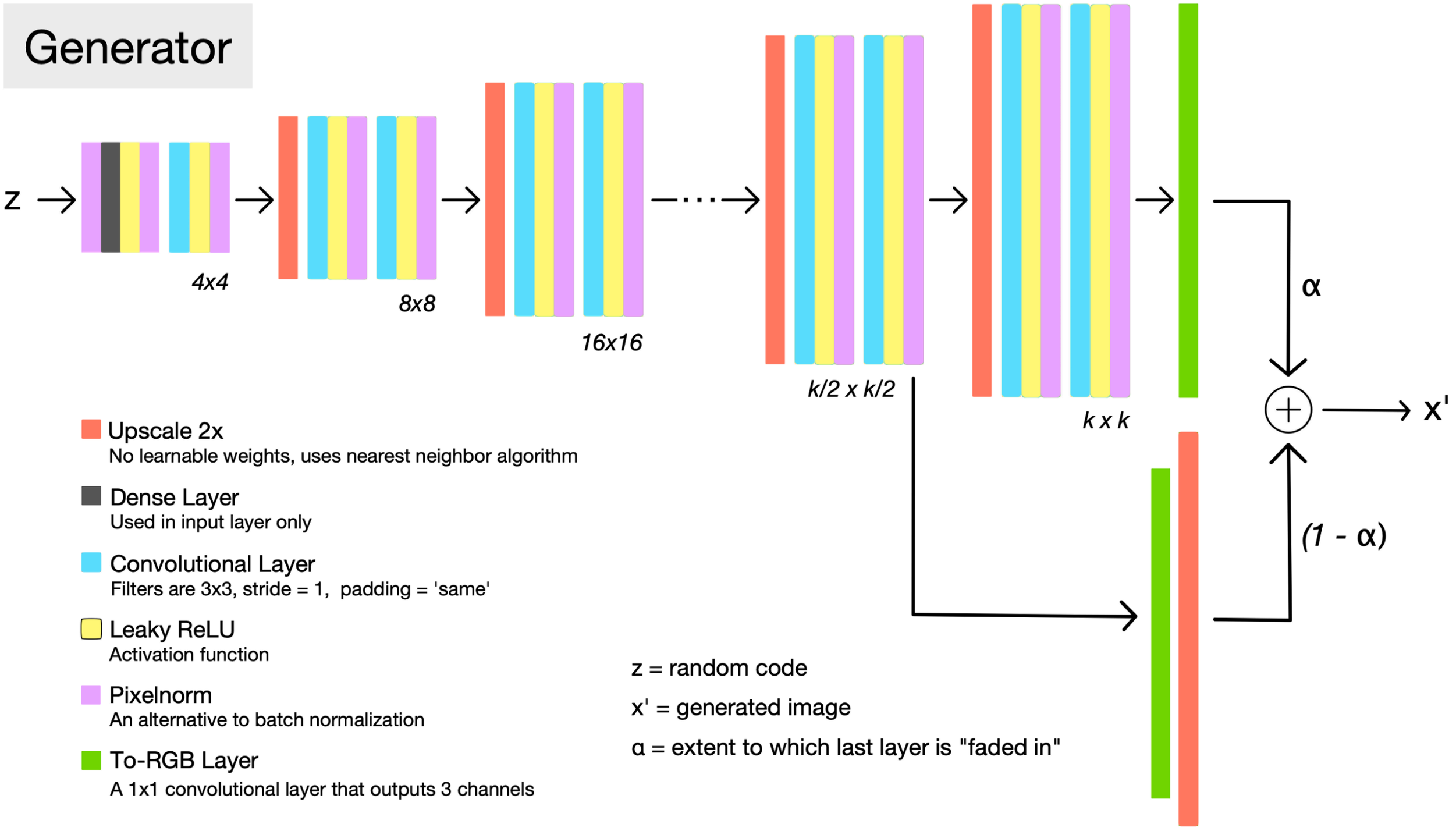
Pixel Normalization

Instead of using batch normalization, as is commonly done, the authors used *pixel normalization*. This "pixelnorm" layer has no trainable weights. It normalizes the feature vector in each pixel to unit length, and is applied after the convolutional layers in the generator. This is done to prevent signal magnitudes from spiraling out of control during training.

$$b_{x,y}^{j} = \frac{a_{x,y}^{j}}{\sqrt{\frac{1}{C}\sum_{j=0}^{C} a_{x,y}^{j\,2} + \epsilon}}$$

The values of each pixel (x, y) across C channels are normalized to a fixed length. Here, **a** is the input tensor, **b** is the output tensor, and **ε** is a small value to prevent dividing by zero.

Generator



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  Activation function
- **Pixelnorm**
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  A 1x1 convolutional layer that outputs 3 channels

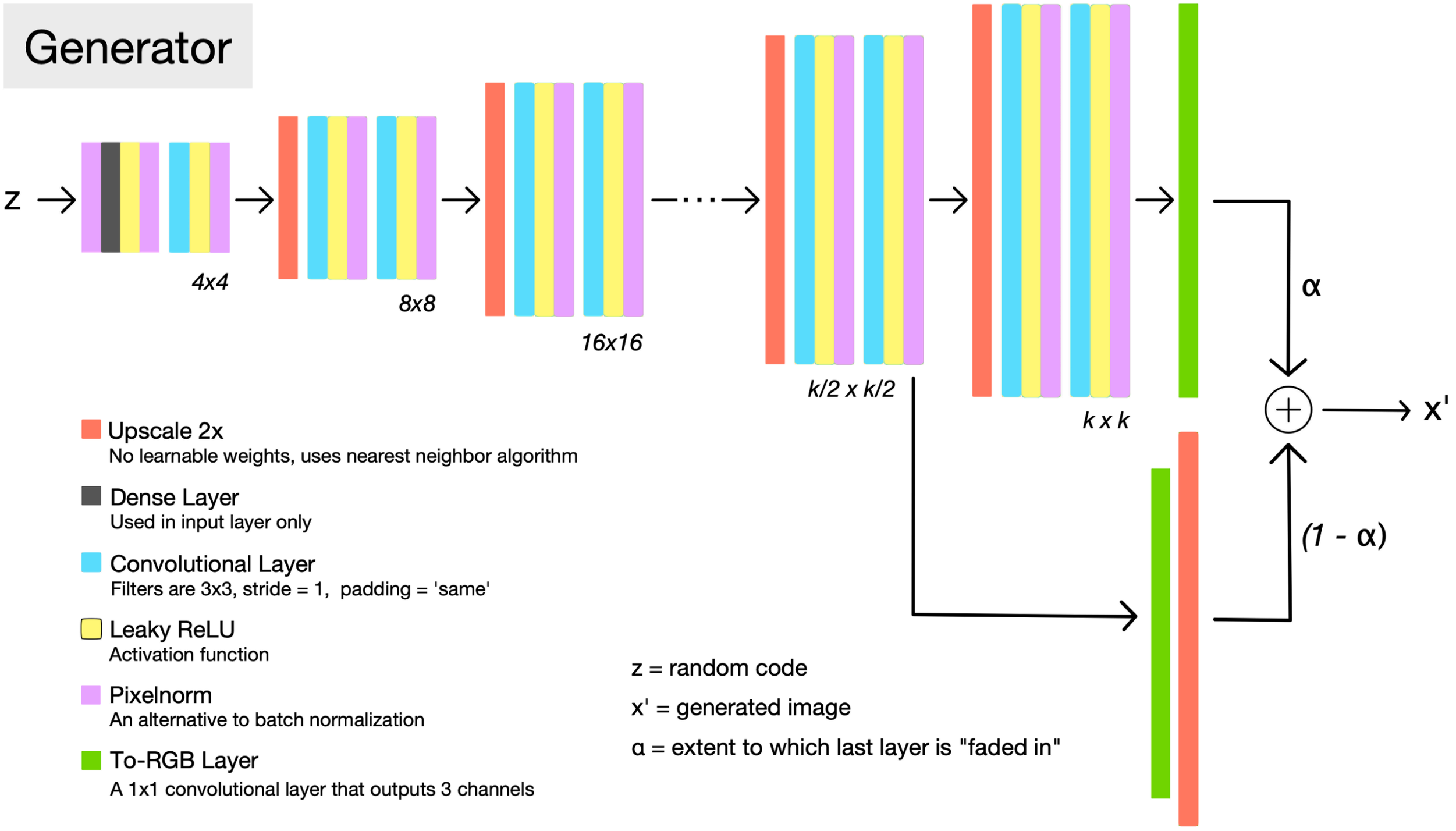
z = random code

x' = generated image

α = extent to which last layer is "faded in"

Fade in

Generator



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  Activation function
- **Pixelnorm**
  An alternative to batch normalization
- **To-RGB Layer**
  A 1x1 convolutional layer that outputs 3 channels

z = random code

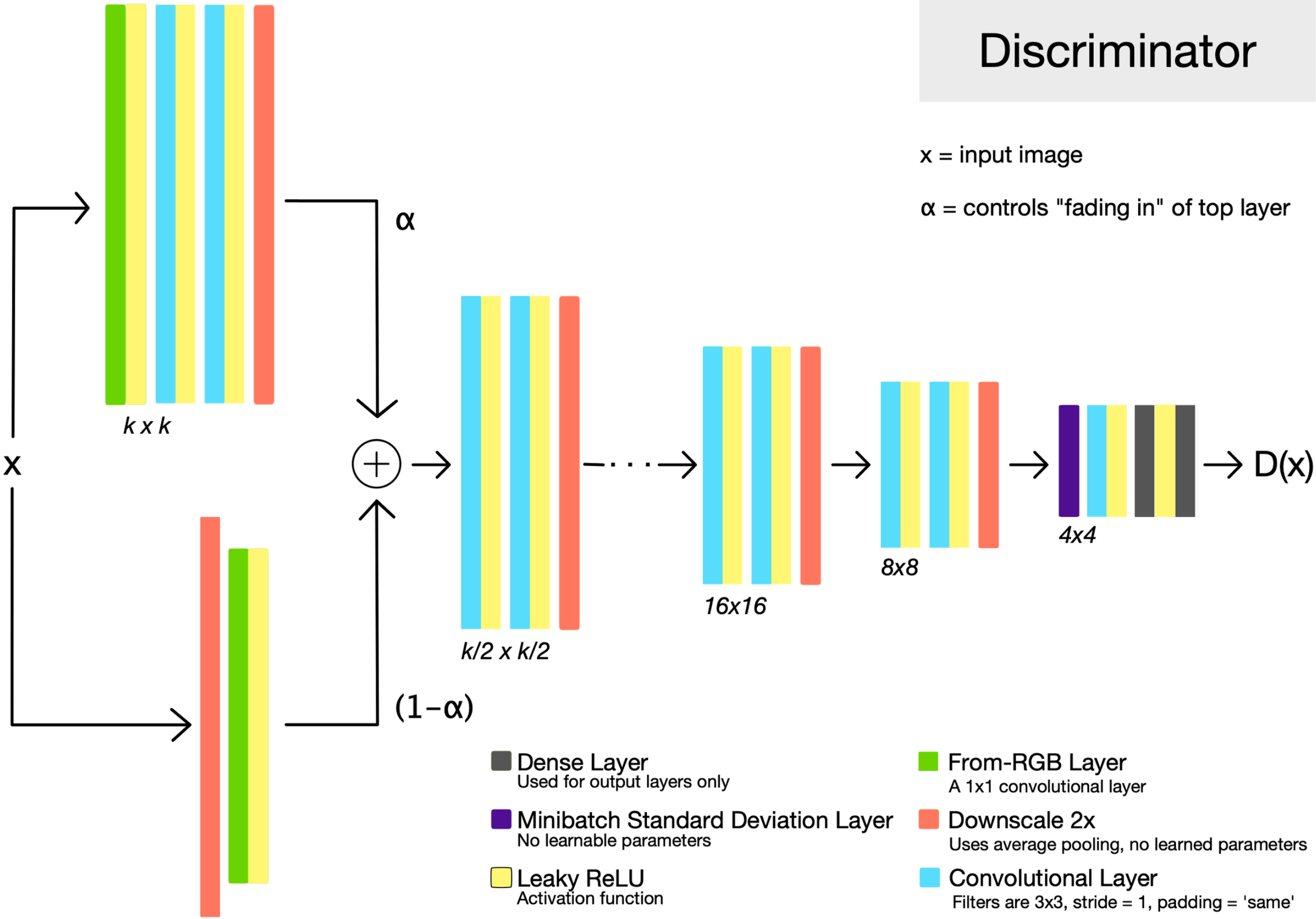
x' = generated image

α = extent to which last layer is "faded in"

Discriminator

x = input image

α = controls "fading in" of top layer



Minibatch standard deviation

- The details don’t matter much, but the core idea is this:
- We’d like to avoid the generator creating beautiful but identical pictures. (See *mode collapse*.)
- So we score how diverse our generated minibatch is, based on a higher layer activation map of the discriminator.
- We add this score as another loss term.

Gradient regularization

$$Loss_G = -D(x')$$

$$GP = (\|\nabla D(ax' + (1-a)x))\|_2 - 1)^2$$

$$Loss_D = -D(x) + D(x') + \lambda * GP$$

- Don’t mind the particular formula (WGAN-GP, Gulrajani et al), here is the intuition:
- Usually our optimizer calculates gradients of the loss with respect to the neural weights, so we don’t have to deal with gradients explicitly.
- This time we calculate gradients of the loss with respect to the ***input***.
- We use this to quantify how smooth the input-output mapping of our network is.
- The optimizer then calculates the gradients of this smoothness metric with respect to neural weights, as usual.

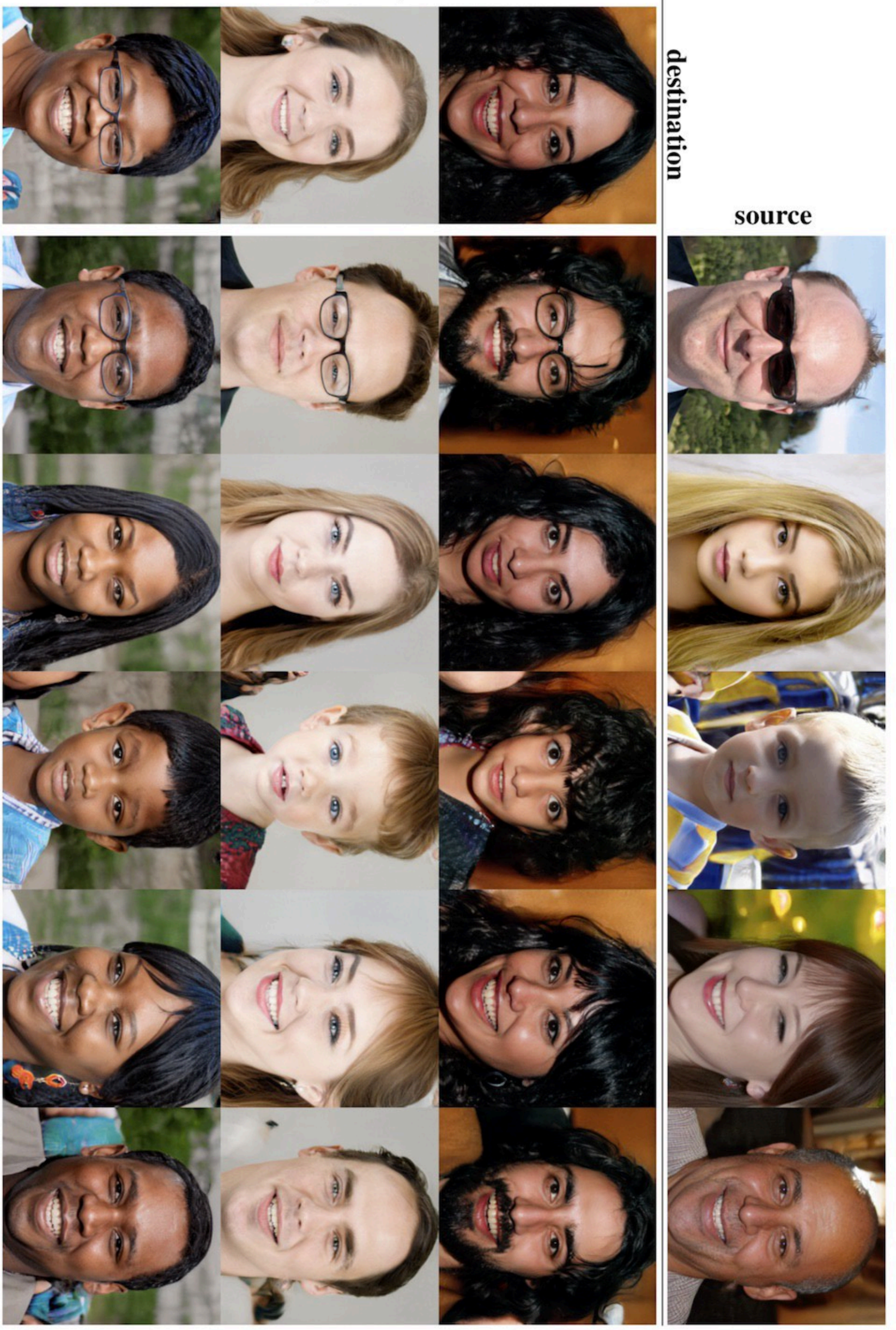
StyleGAN

2018 December

Coarse styles copied

destination

source



Fine from B

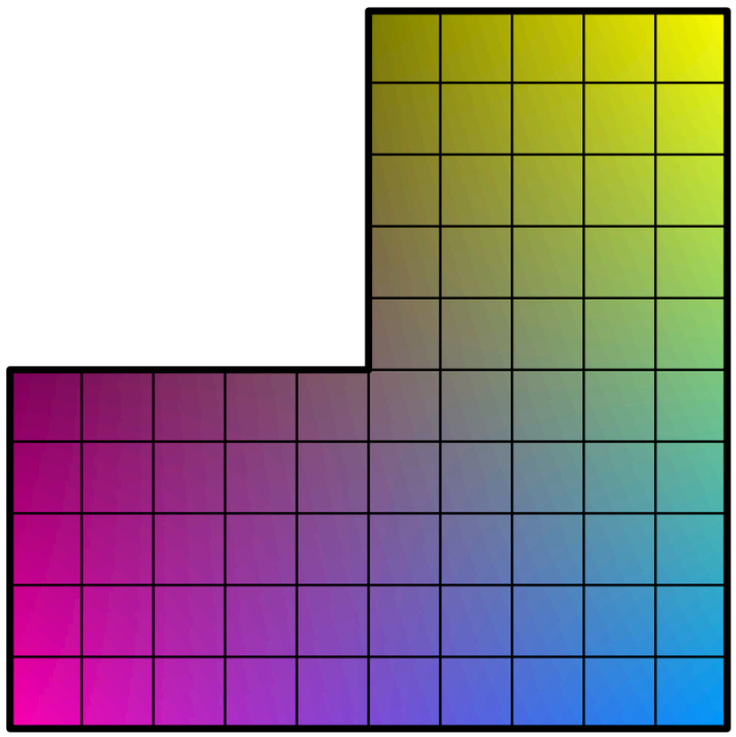
Middle styles from source B

Coarse styles from source B

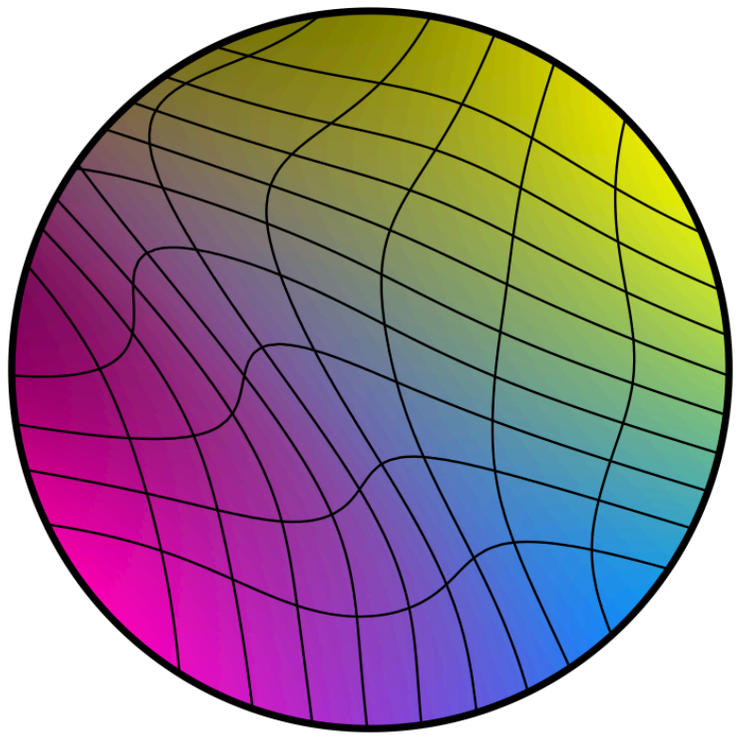
Source A

Source B

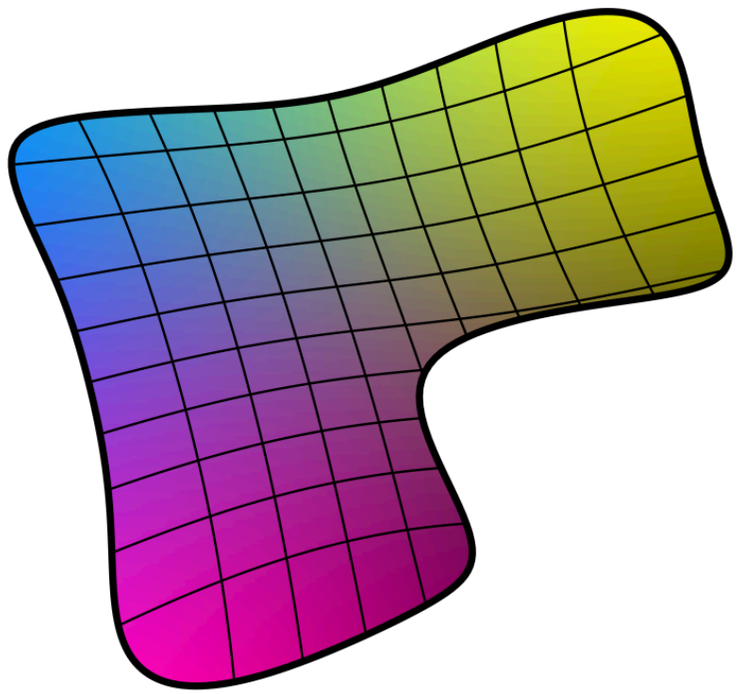
Intermediate latent space W



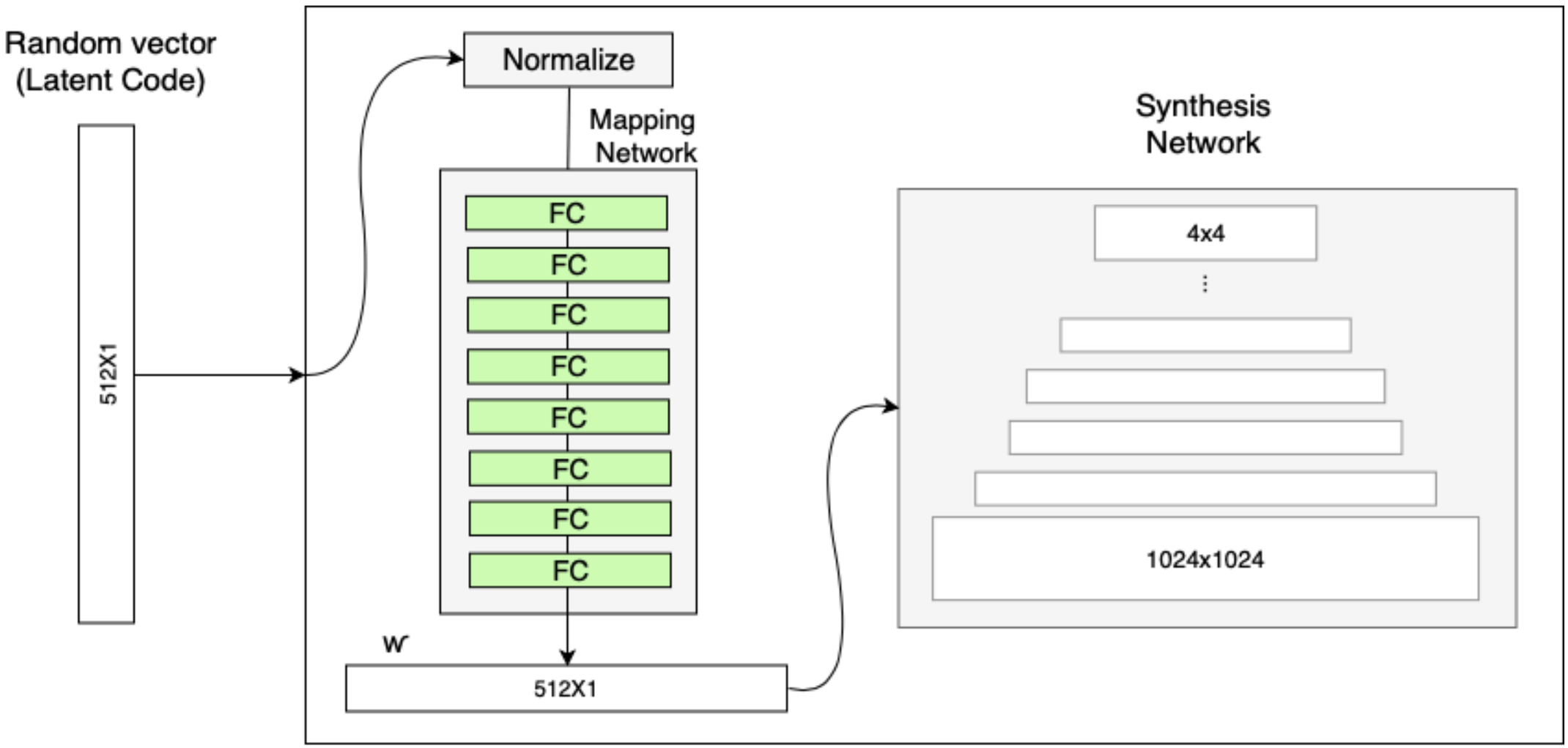
(a) Distribution of features in training set



(b) Mapping from $\mathcal{Z}$ to features

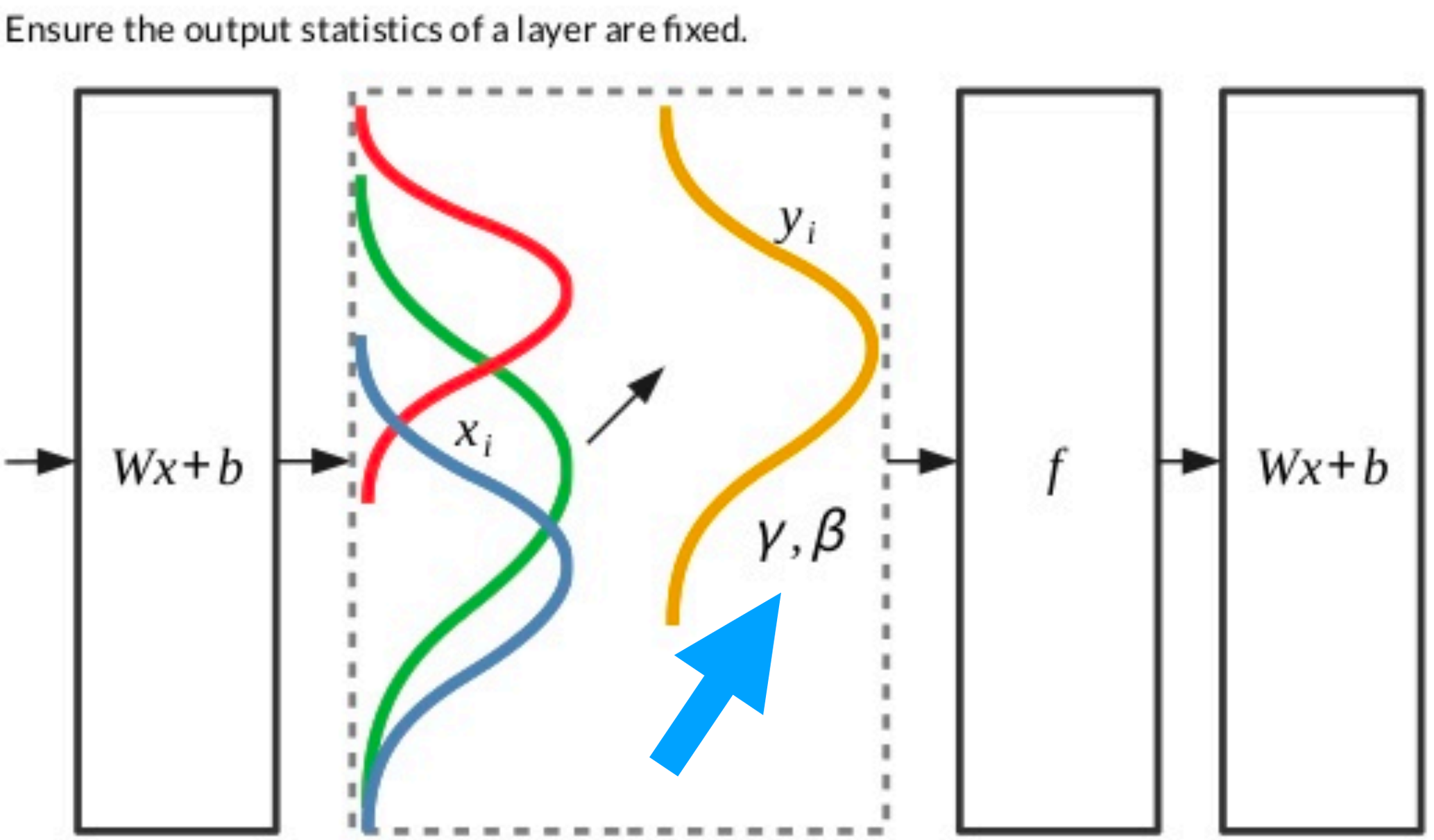


(c) Mapping from $\mathcal{W}$ to features


Random vector
(Latent Code)
512X1
Normalize
Mapping
Network
FC
FC
FC
FC
FC
FC
w
512X1
Synthesis
Network
4x4
1024x1024

Adaptive Instance Normalization

Batch normalization reminder



Style transfer









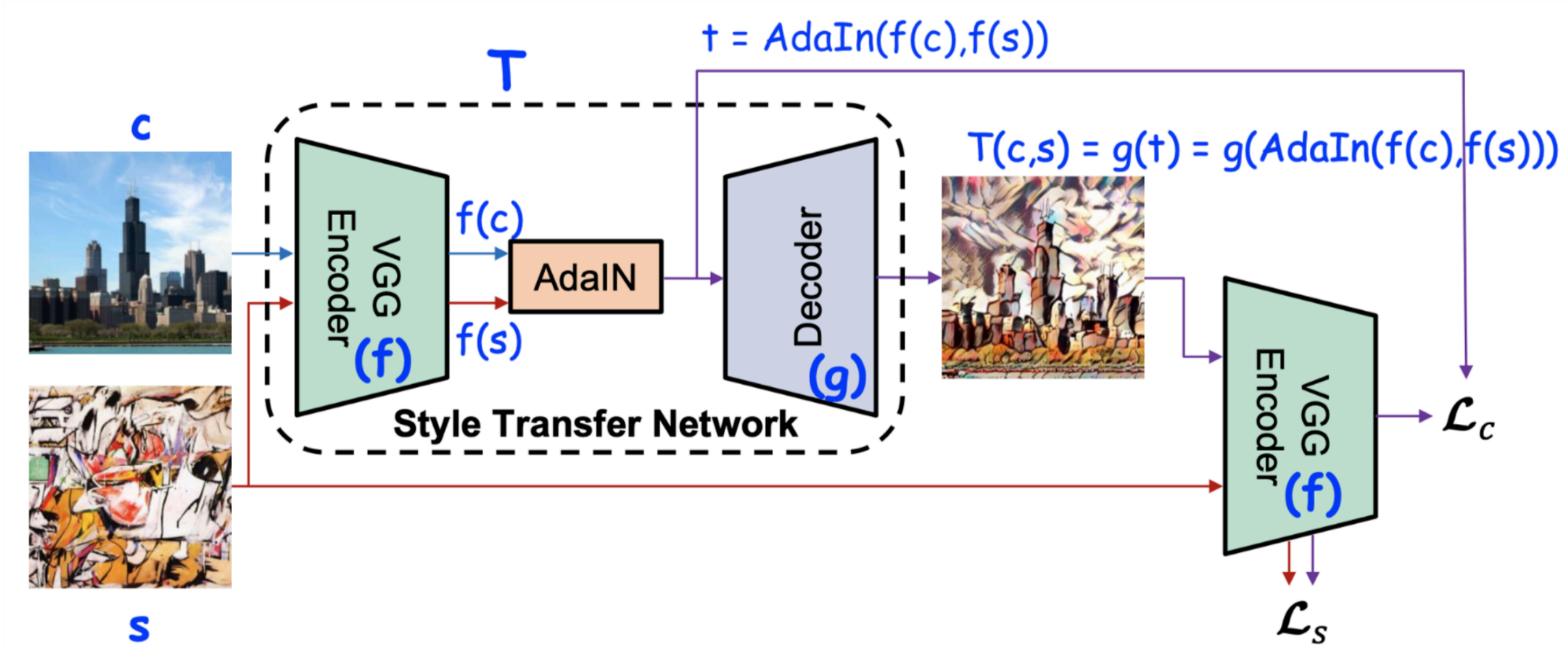




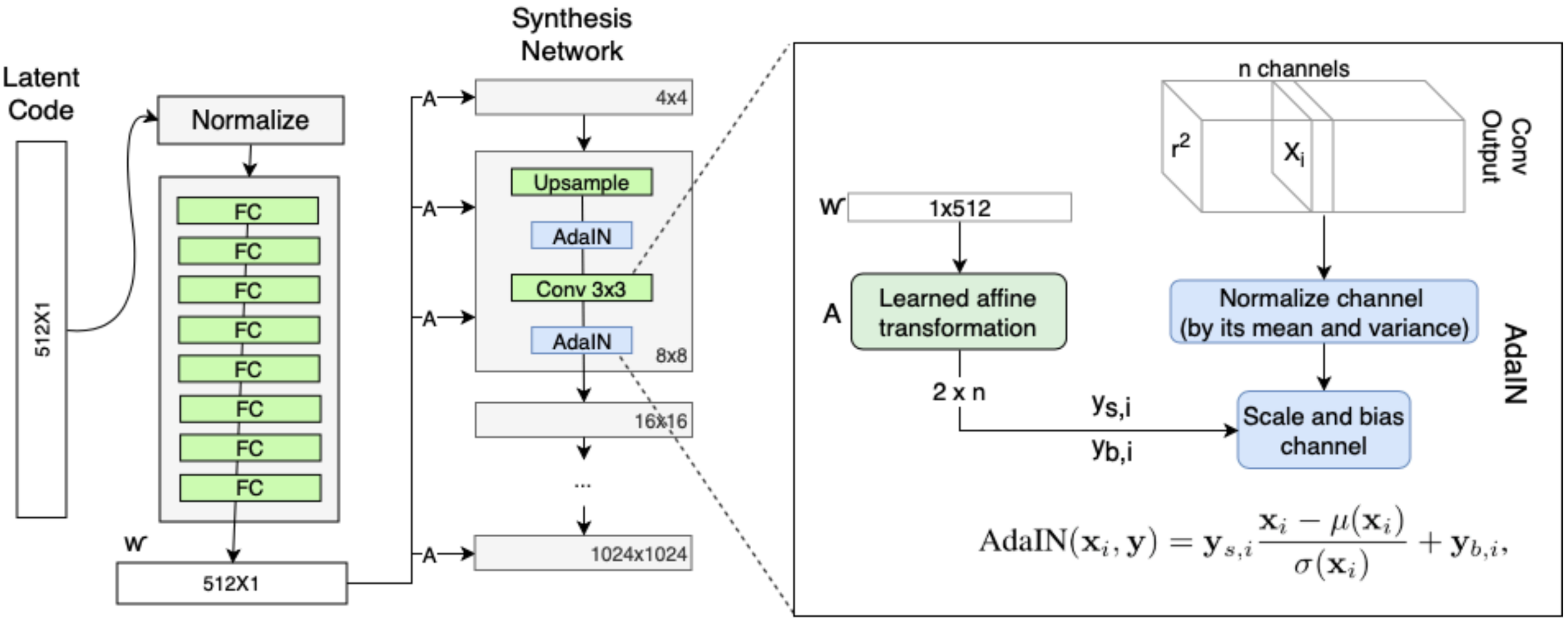




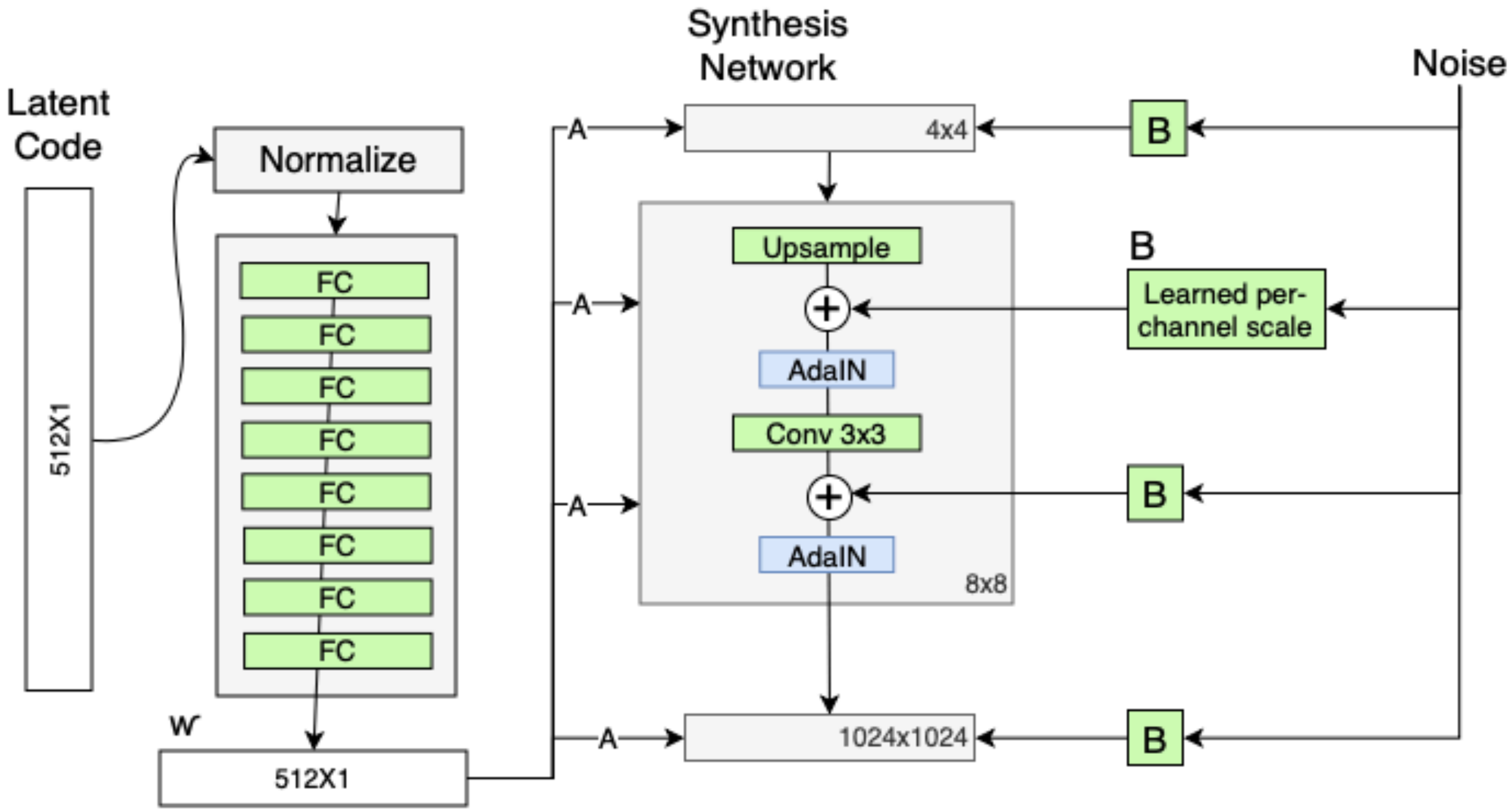

AdaIN for style transfer

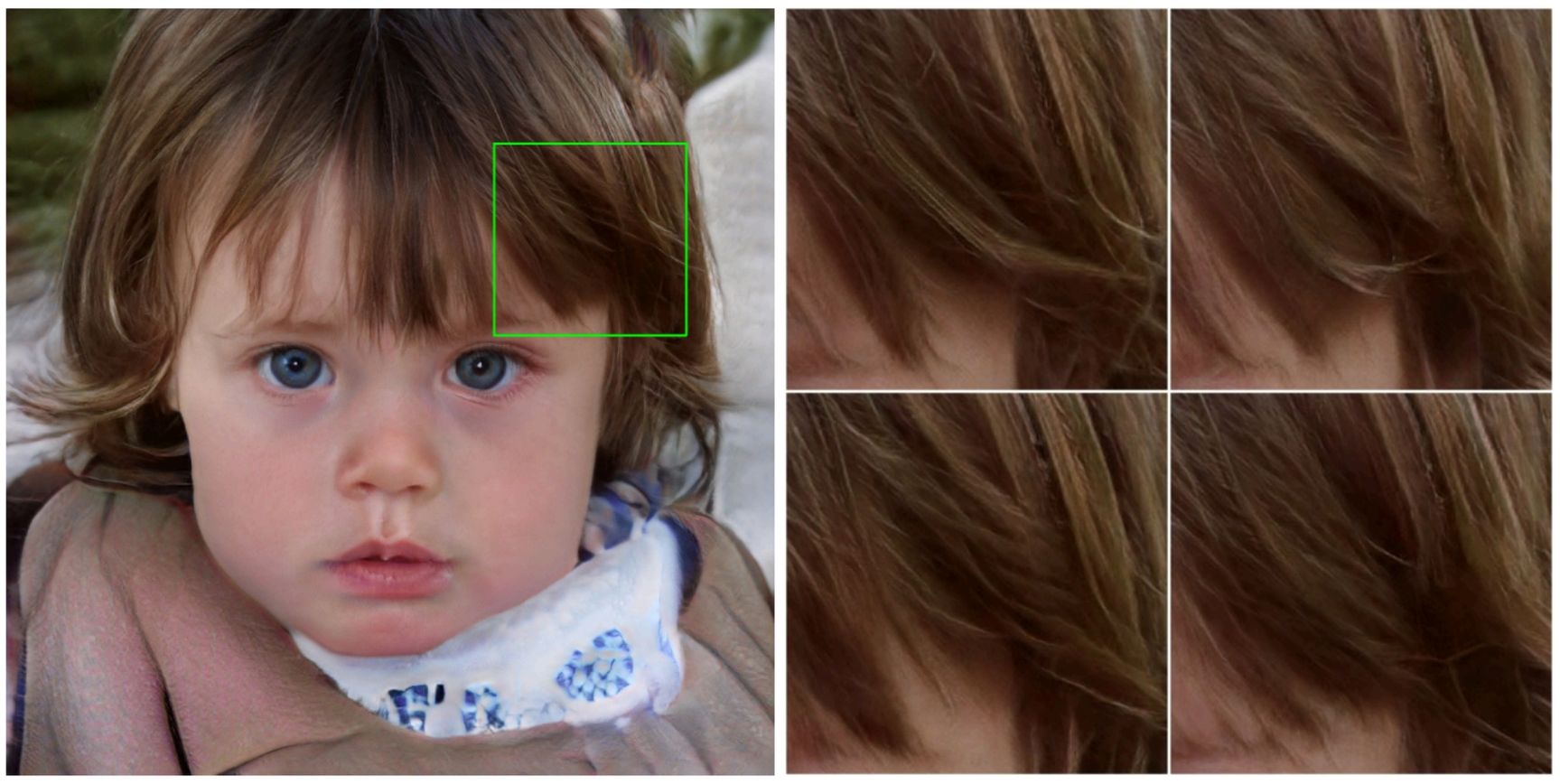


AdaIN in StyleGAN



Noise input


Latent Code
512X1
Normalize
FC
FC
FC
FC
FC
FC
FC
w
512X1
Synthesis Network
A
4x4
B
Noise
Upsample
B
Learned per-channel scale
A
AdaIN
Conv 3x3
A
B
AdaIN
8x8
A
1024x1024
B



Generator

Random vector
(Latent Code)

512X1

Normalize

Mapping
network f

FC
FC
FC
FC
FC
FC
FC
FC

$w \in W$

Synthesis network g

Noise

Const 4×4×512

B

A

style

AdaIN

Conv 3×3

4×4

Upsample

8×8

...

1024x1024

Training

ProGAN
Discriminator

1024x1024

...

4x4

Loss
(e.g. WGAN-GP)

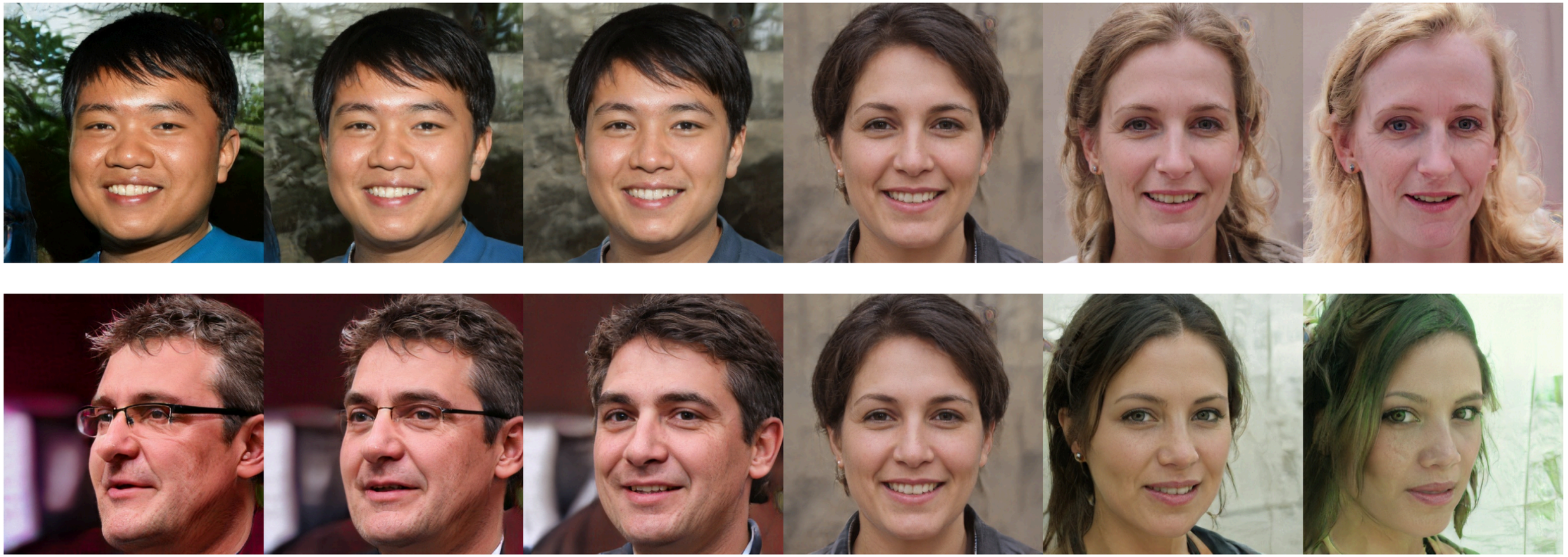
Real Sample

Downscaling

Training

Truncation trick in W

(it’s shrinking, really)



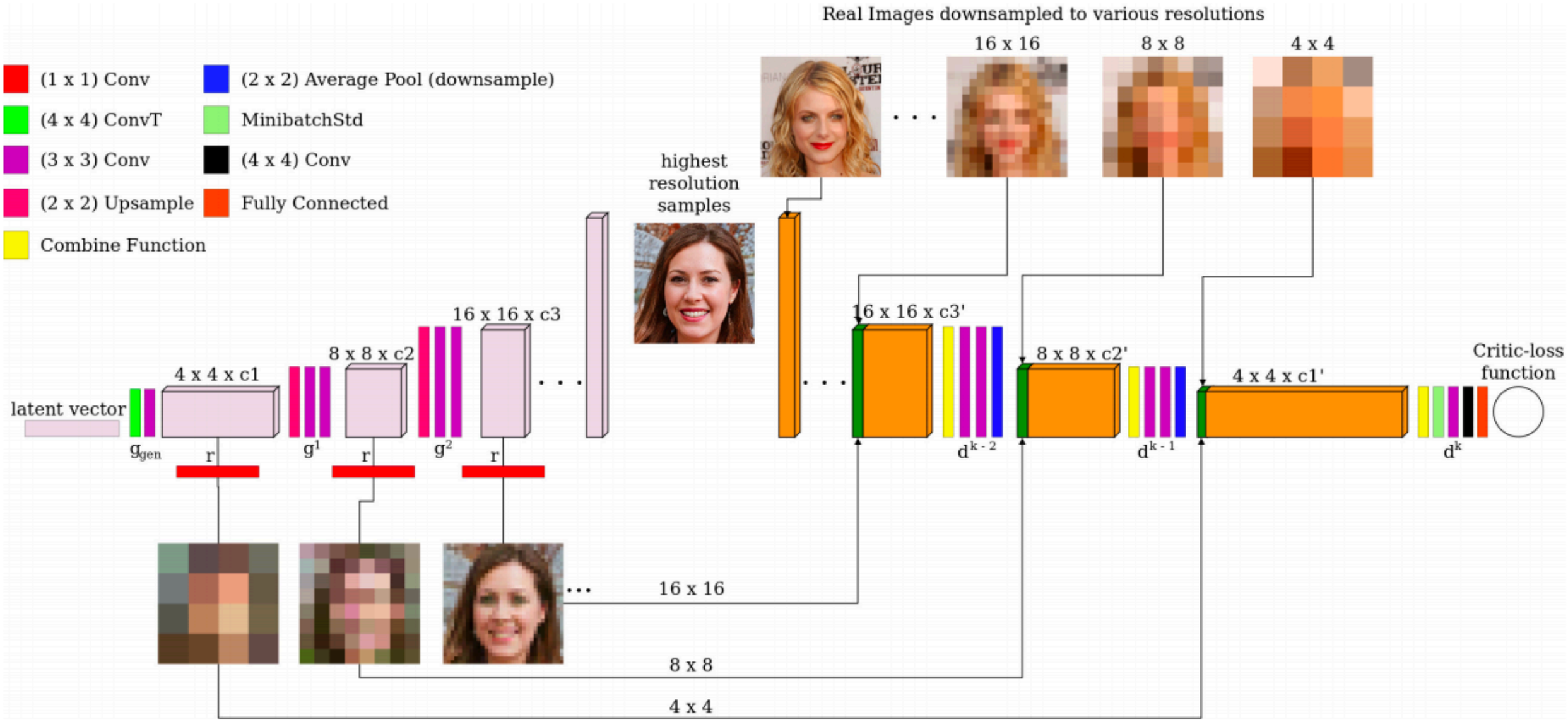
$\psi = 1$ $\psi = 0.7$ $\psi = 0.5$ $\psi = 0$ $\psi = -0.5$ $\psi = -1$

StyleGAN2

2019 December

(very briefly)

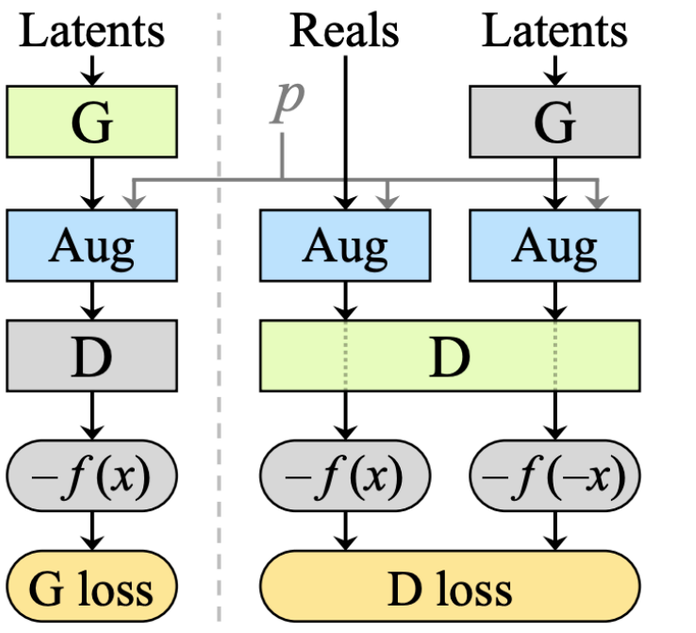
Getting rid of progressive growing: Multi-Scale Gradients

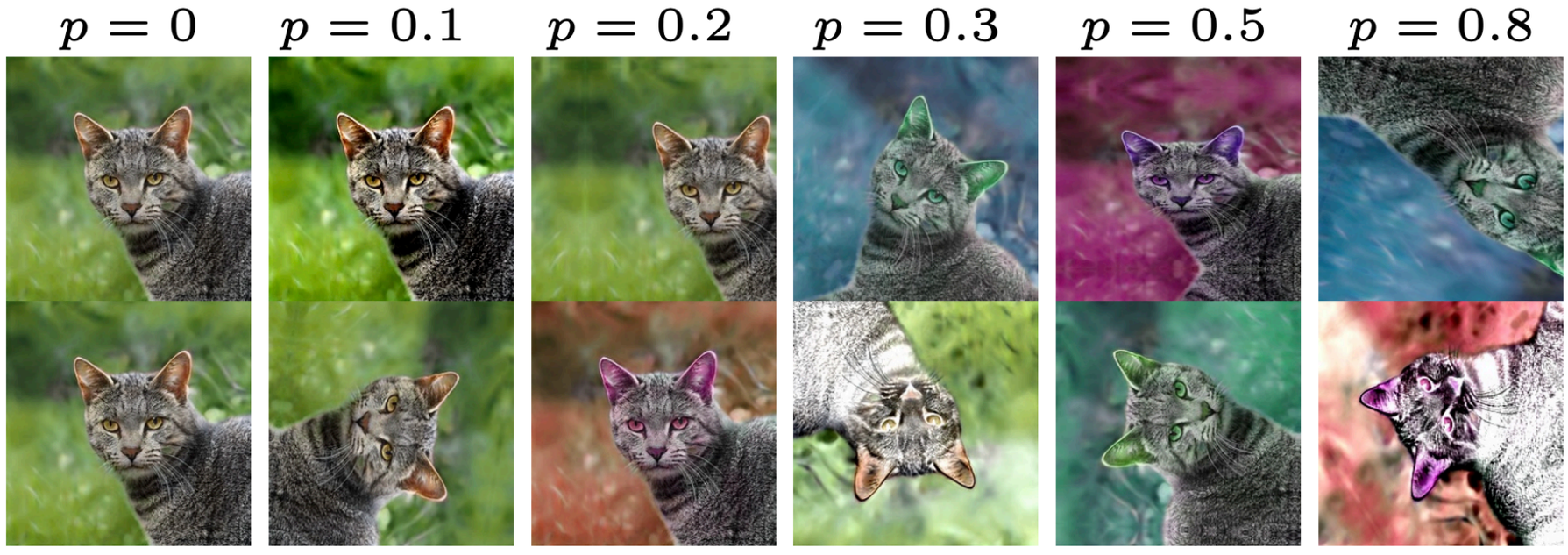


Adaptive Discriminator Augmentation,

2020 June

(super briefly)


Latents
Reals
Latents
G
p
G
Aug
Aug
Aug
D
D
−f(x)
−f(x)
−f(−x)
G loss
D loss


p = 0
p = 0.1
p = 0.2
p = 0.3
p = 0.5
p = 0.8

Pixel blitting

x-flip

90° rotations

Integer translation

General geometric transformations

Isotropic scaling

Arbitrary rotation

Anisotropic scaling

Fractional translation

Color transformations

Brightness

Contrast

Luma flip

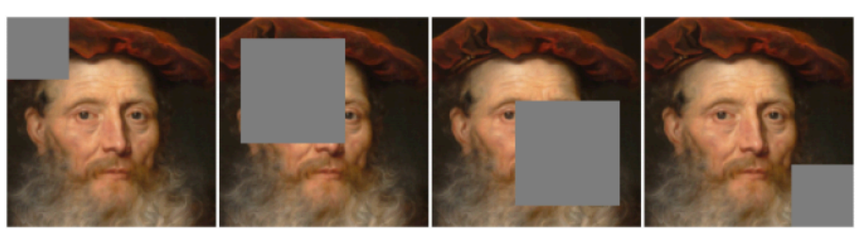
Hue rotation

Saturation

Image-space corruptions

Additive RGB noise

Cutout



Homework:
latent space arithmetics

https://colab.research.google.com/drive/1OxRHEfaZvqC_CkbSFctTzjrCLrh_JsHE