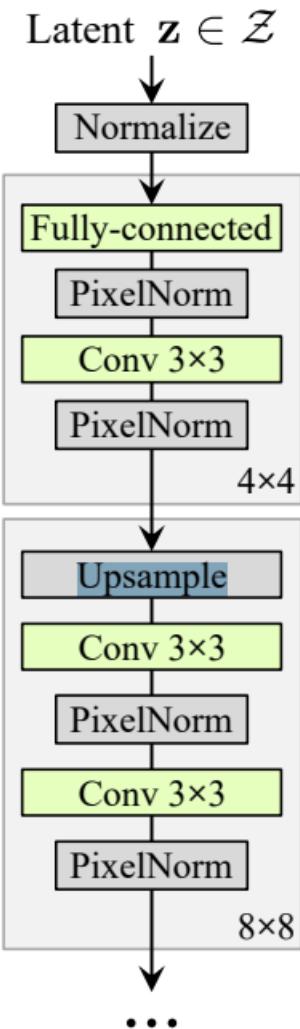


A Style-Based Generator Architecture for Generative Adversarial Networks

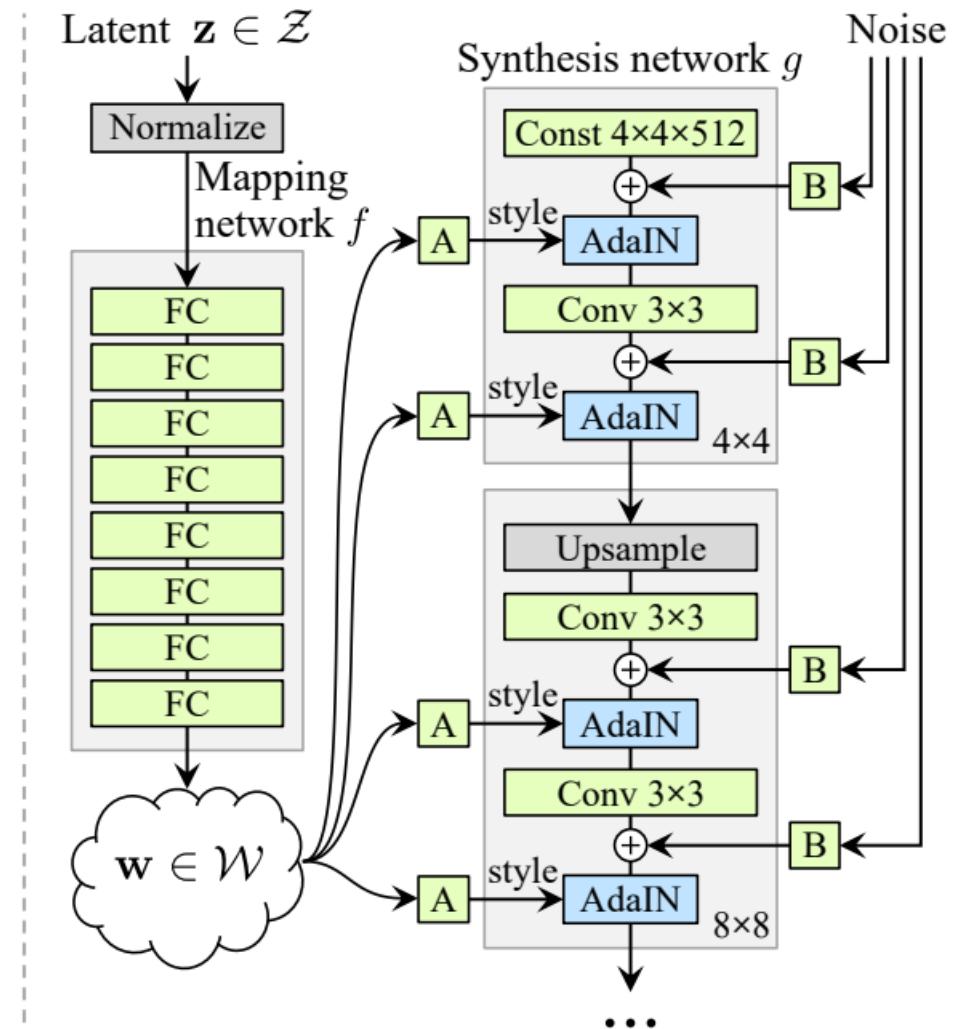
Корягин Никита

Motivation

Хотим поменять архитектуру генератора в GAN, чтобы контролировать процесс генерации



(a) Traditional



(b) Style-based generator

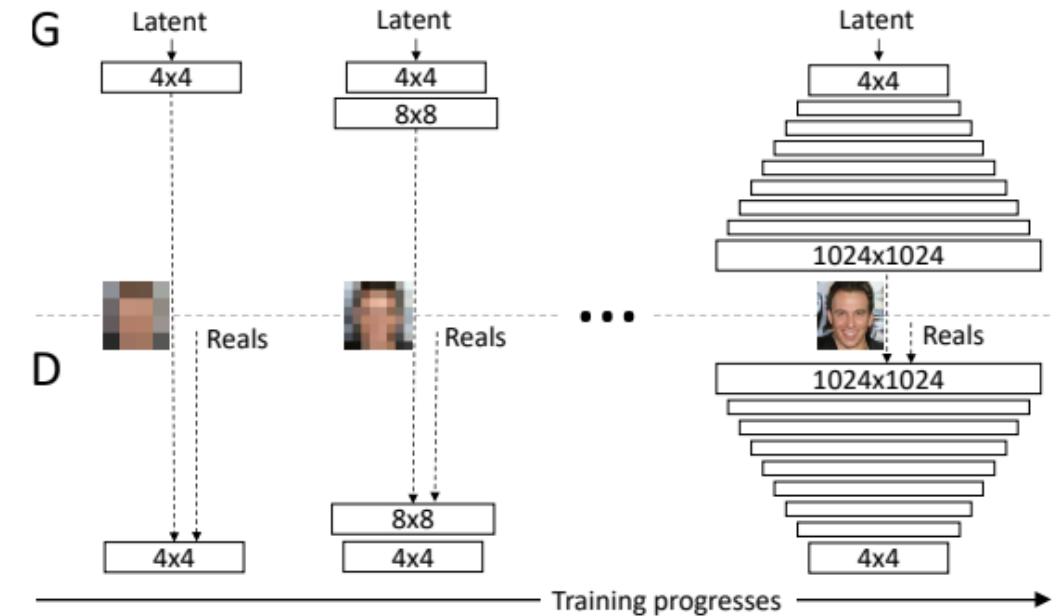
Architecture StyleGAN

ProGAN

Обучение начинается с генератором и дискриминатором маленького разрешения

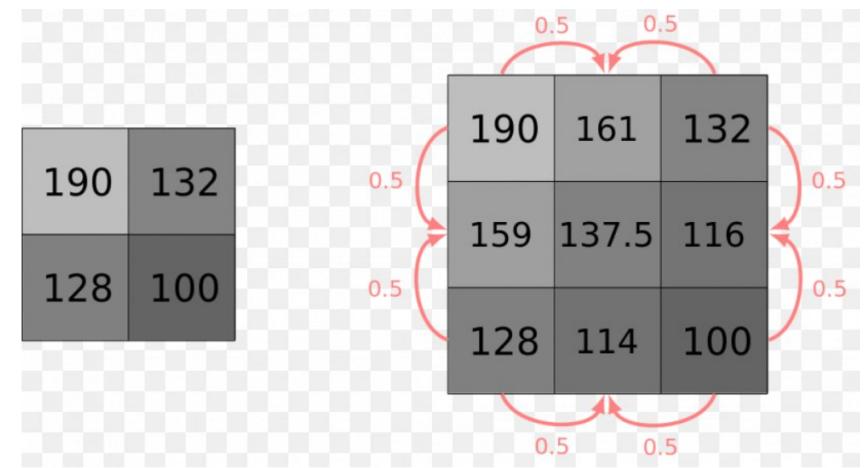
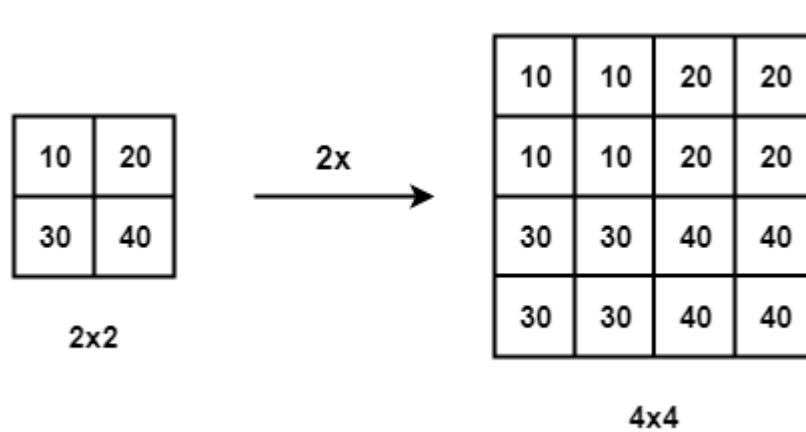
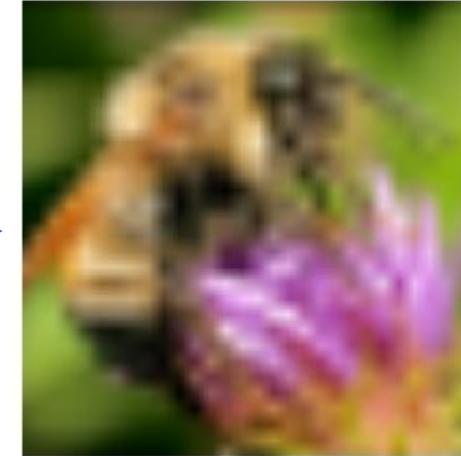
В процессе обучения добавляются новые слои

Это позволяет добиться стабилизации изображений и ускоряет обучение



Architecture StyleGAN

Nearest Neighbor to Bilinear Sampling

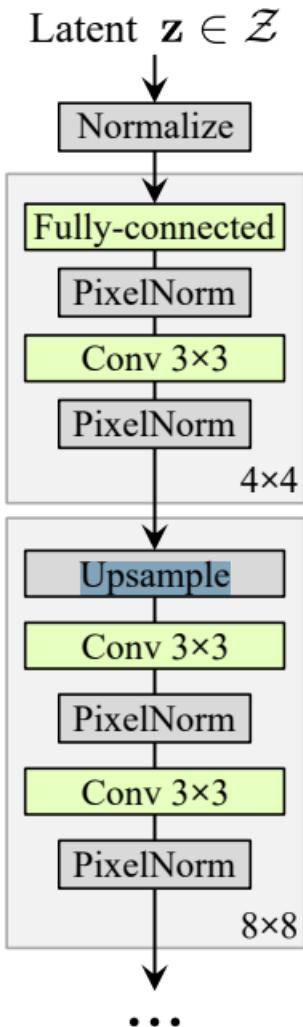


Architecture StyleGAN

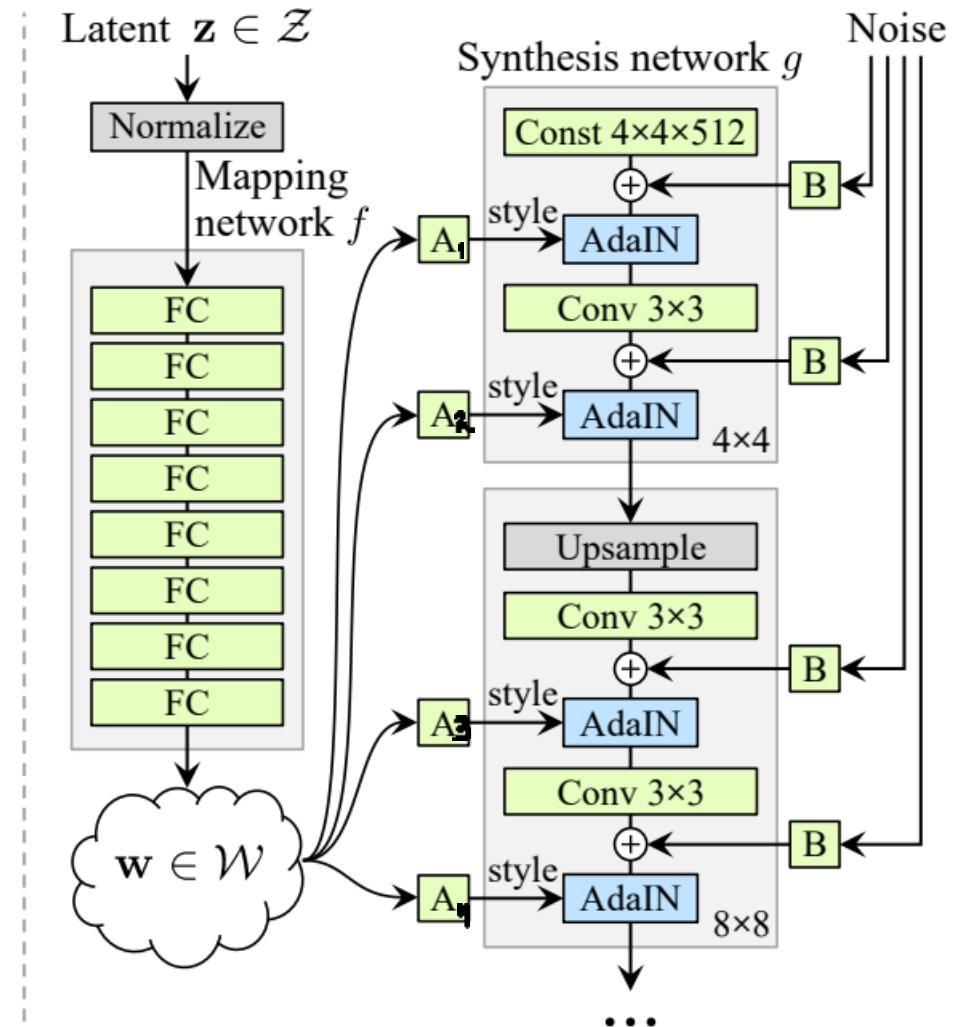
Mapping network & AdaIN operation

$$\text{AdaIN}(\mathbf{x}_i, \mathbf{y}) = \mathbf{y}_{s,i} \frac{\mathbf{x}_i - \mu(\mathbf{x}_i)}{\sigma(\mathbf{x}_i)} + \mathbf{y}_{b,i},$$

$$\mathbf{y} = (\mathbf{y}_s, \mathbf{y}_b)$$



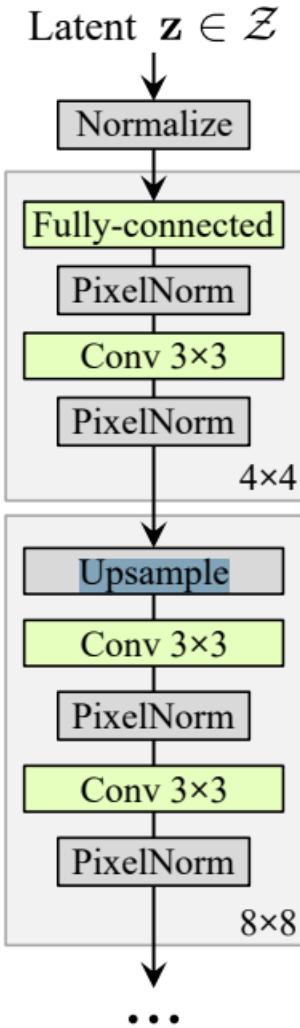
(a) Traditional



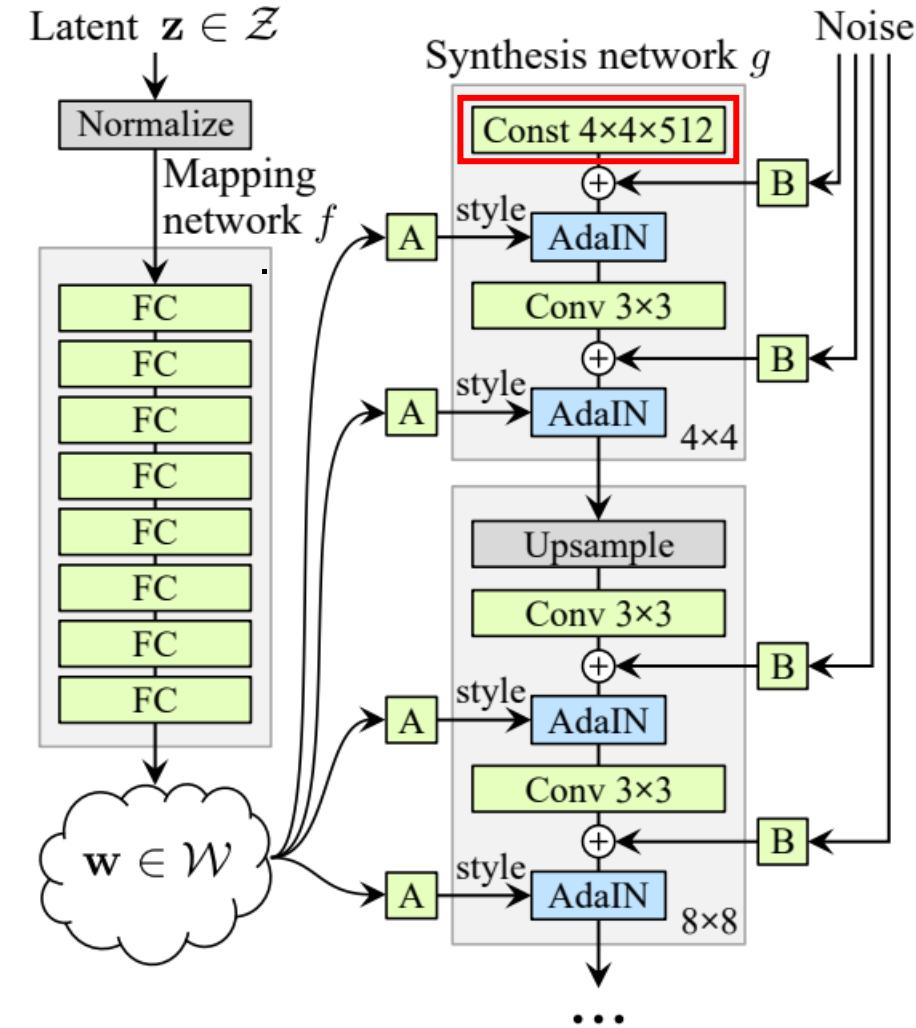
(b) Style-based generator

Architecture StyleGAN

Remove traditional input & Add random noise



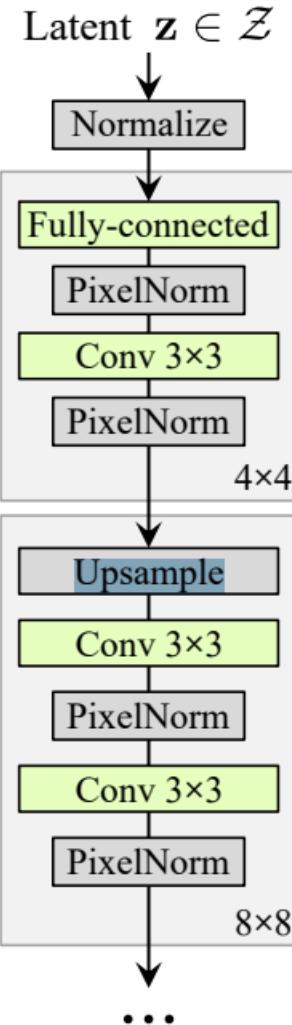
(a) Traditional



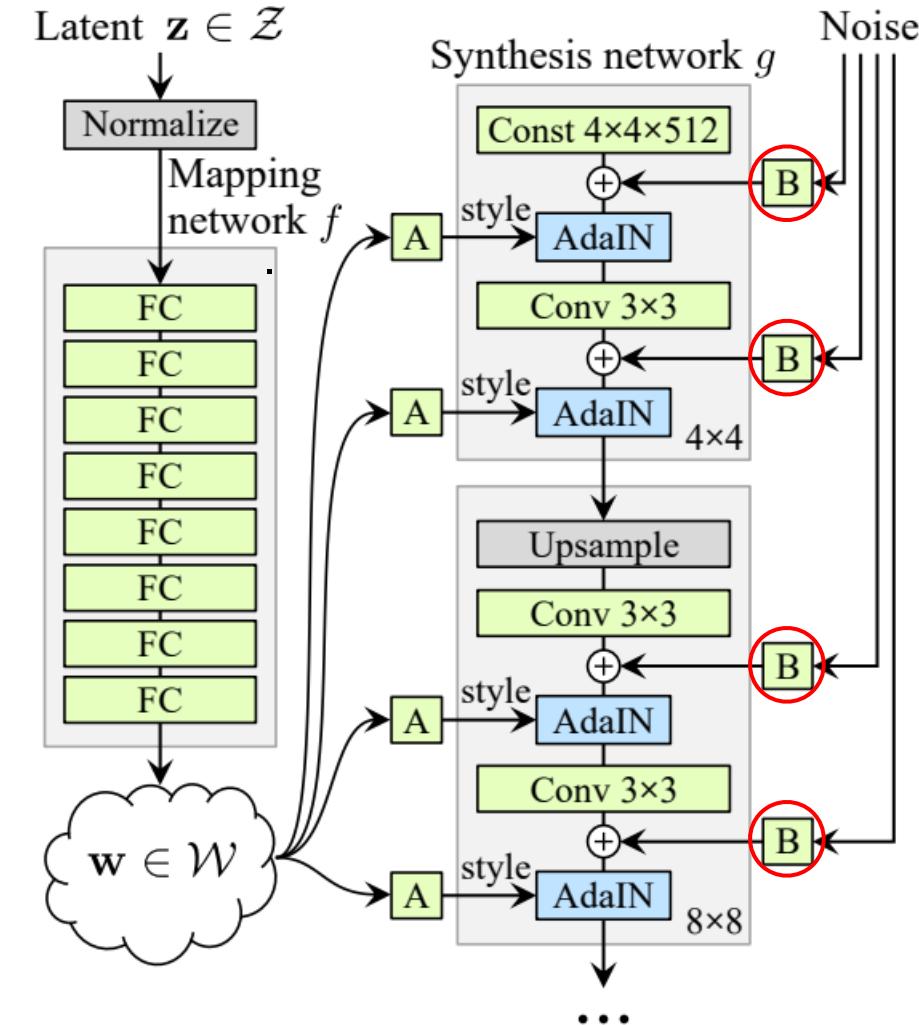
(b) Style-based generator

Architecture StyleGAN

Remove traditional input & Add random noise



(a) Traditional

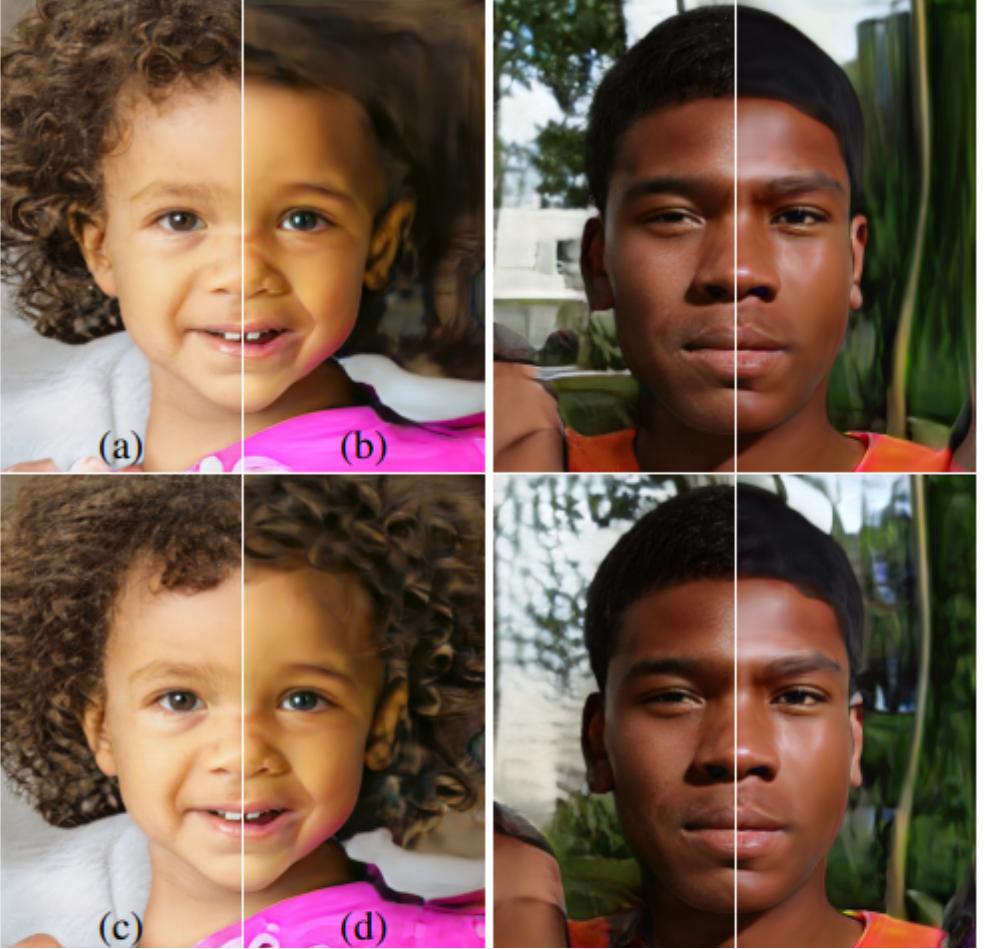


(b) Style-based generator

Architecture StyleGAN

Remove traditional input & Add random noise

Figure 5. Effect of noise inputs at different layers of our generator. (a) Noise is applied to all layers. (b) No noise. (c) Noise in fine layers only ($64^2 - 1024^2$). (d) Noise in coarse layers only ($4^2 - 32^2$). We can see that the artificial omission of noise leads to featureless “painterly” look. Coarse noise causes large-scale curling of hair and appearance of larger background features, while the fine noise brings out the finer curls of hair, finer background detail, and skin pores.



Architecture StyleGAN

StyleMixing

Latent $\mathbf{z} \in \mathcal{Z}$

Normalize

Fully-connected

PixelNorm

Conv 3×3

PixelNorm

4×4

Upsample

Conv 3×3

PixelNorm

Conv 3×3

PixelNorm

8×8

...

(a) Traditional

Latent $\mathbf{z} \in \mathcal{Z}$

Normalize

Mapping network f

FC

FC

FC

FC

FC

FC

FC

w ∈ \mathcal{W}

Synthesis network g

Const 4×4×512

AdaIN

Conv 3×3

AdaIN

4×4

Upsample

Conv 3×3

AdaIN

Conv 3×3

AdaIN

8×8

Noise

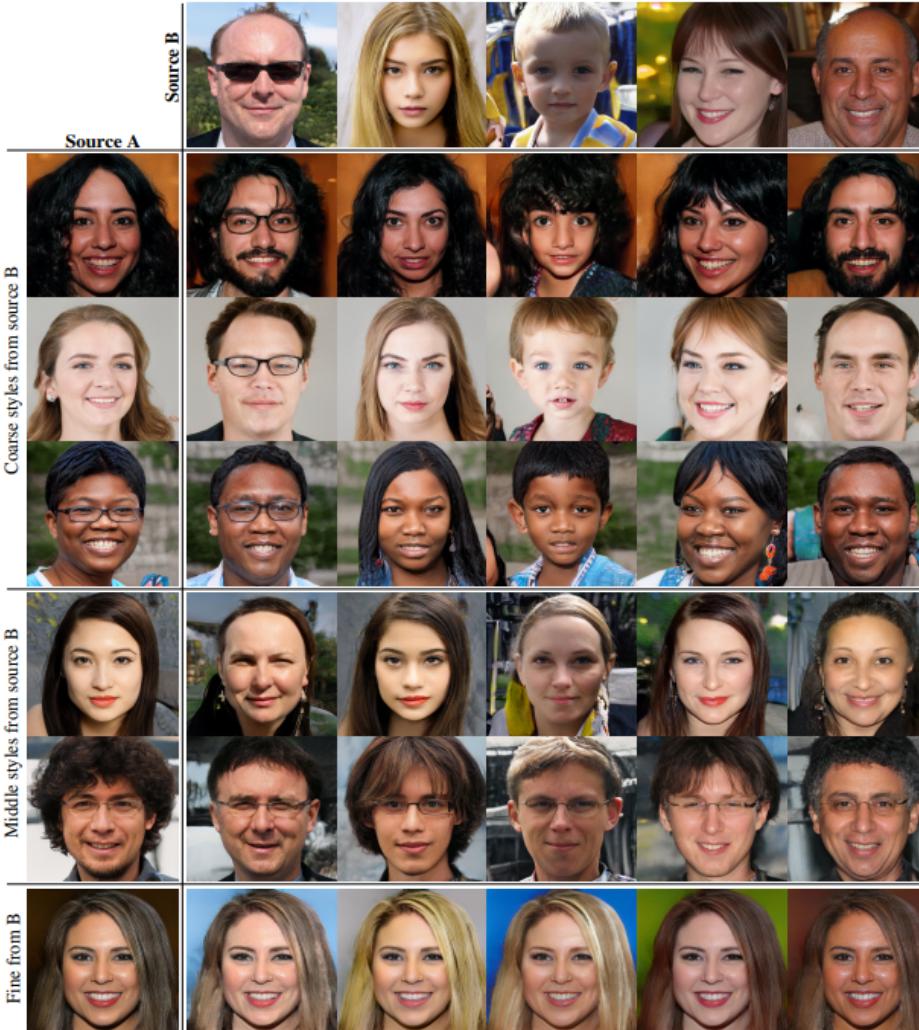
A

B

(b) Style-based generator

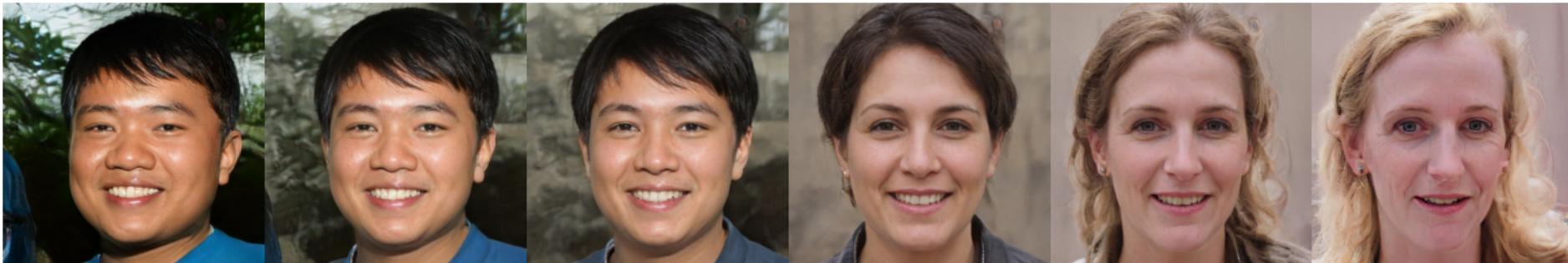
Architecture StyleGAN

StyleMixing



Properties of StyleGAN

Control the image synthesis



$\psi = 1$

$\psi = 0.7$

$\psi = 0.5$

$\psi = 0$

$\psi = -0.5$

$\psi = -1$

Properties of StyleGAN

Separation of global effects from stochasticity

Figure 4. Examples of stochastic variation. (a) Two generated images. (b) Zoom-in with different realizations of input noise. While the overall appearance is almost identical, individual hairs are placed very differently. (c) Standard deviation of each pixel over 100 different realizations, highlighting which parts of the images are affected by the noise. The main areas are the hair, silhouettes, and parts of background, but there is also interesting stochastic variation in the eye reflections. Global aspects such as identity and pose are unaffected by stochastic variation.



Truncation Trick



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

$$\mathbf{w}' = \bar{\mathbf{w}} + \psi(\mathbf{w} - \bar{\mathbf{w}}), \text{ where } \psi < 1$$

Results

Method	CelebA-HQ	FFHQ
A Baseline Progressive GAN [30]	7.79	8.04
B + Tuning (incl. bilinear up/down)	6.11	5.25
C + Add mapping and styles	5.34	4.85
D + Remove traditional input	5.07	4.88
E + Add noise inputs	5.06	4.42
F + Mixing regularization	5.17	4.40