

GANs evolution

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Evolution



2014



2015



2016



2017



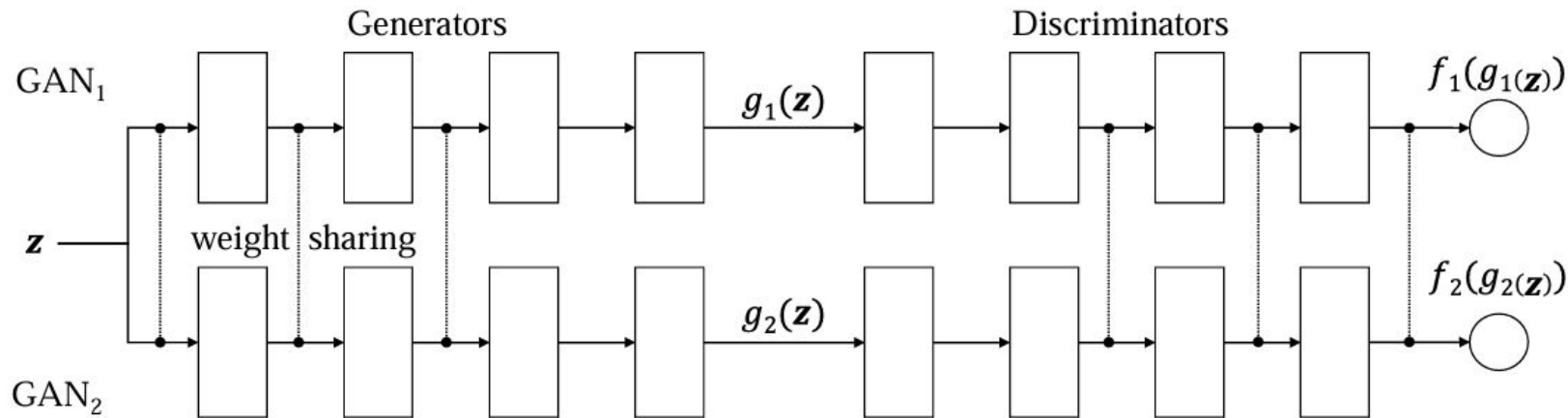
2018

- ▶ **Vanila GAN** <https://arxiv.org/abs/1406.2661>
- ▶ **DCGAN** <https://arxiv.org/abs/1511.06434>
- ▶ **CoGAN** <https://arxiv.org/abs/1606.07536>
- ▶ **ProGAN** <https://arxiv.org/abs/1710.10196>
- ▶ **StyleGAN** <https://arxiv.org/abs/1812.04948>

Deep Convolutional GAN (DCGAN)

- ▶ Introduced CNN into GANs framework
- ▶ Batch normalization
- ▶ **ReLU** and **tanh** for Generator and **LeakyReLU** for Discriminator

Coupled GAN



- ▶ Two generative models G_1 and G_2 , with weight sharing for first layers
- ▶ Two discriminative models F_1 and F_2 , with weight sharing for last layers

Progressive Growing of GANs (ProGAN)

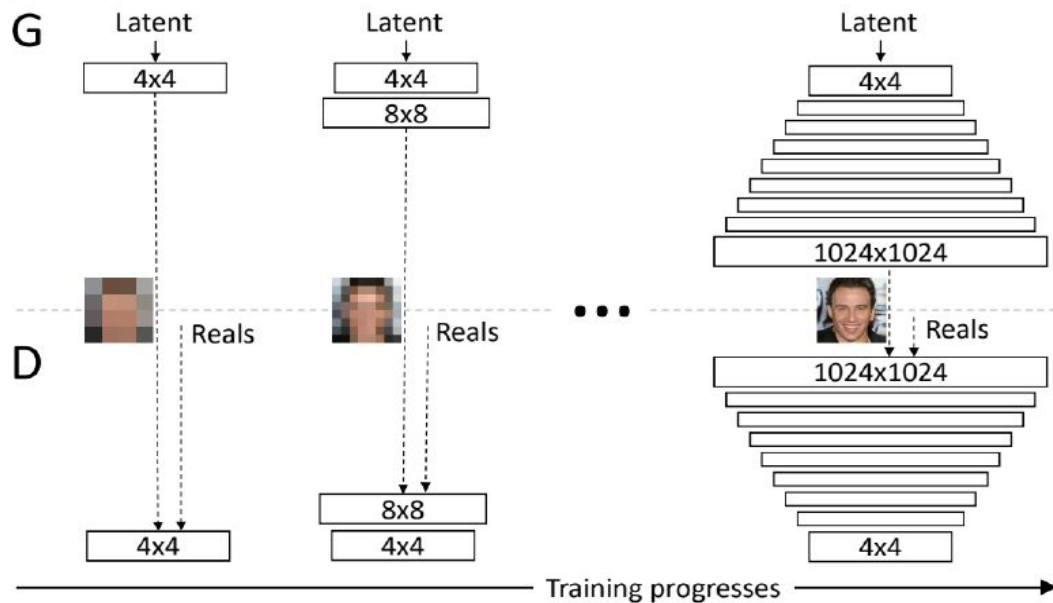
Samples (1024x1024)



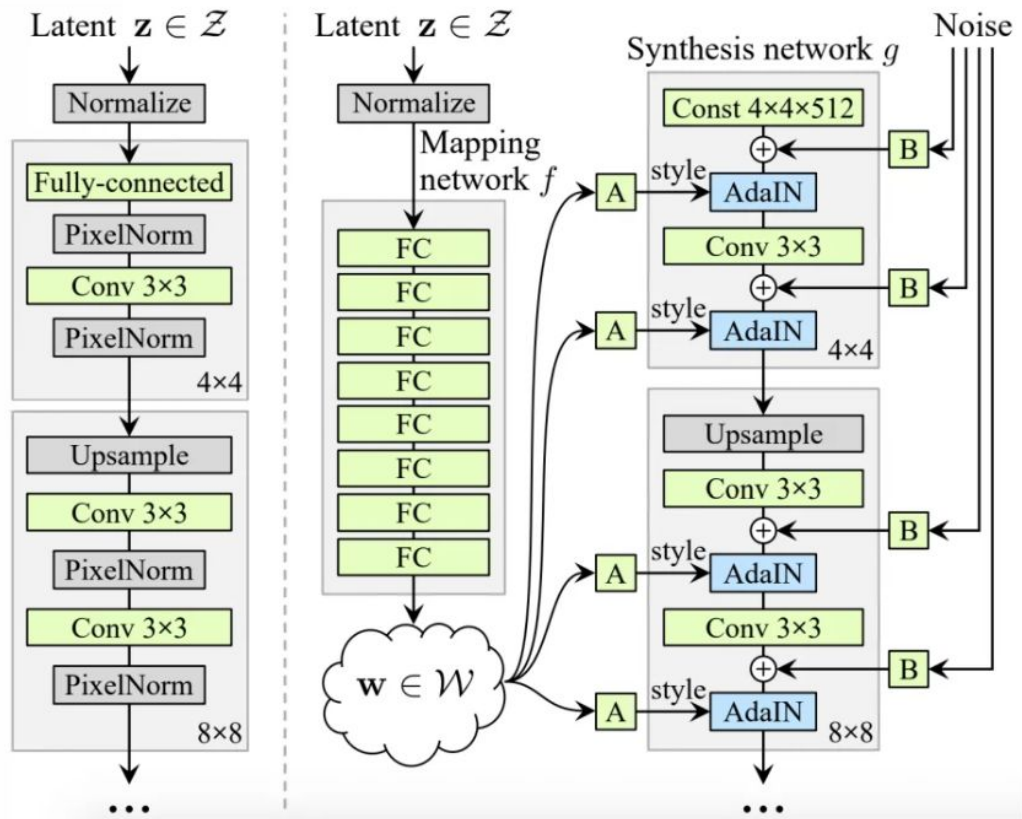
ProGAN

Grow both the generator and discriminator progressively, new layers will introduce higher-resolution details as the training progresses.

- ▶ Train GAN which generate 4x4 images (2 convs for G and D).
- ▶ Add upsampling layers to G, downsampling layers to D.
- ▶ Train GAN which generate 8x8 images.
- ▶ etc.



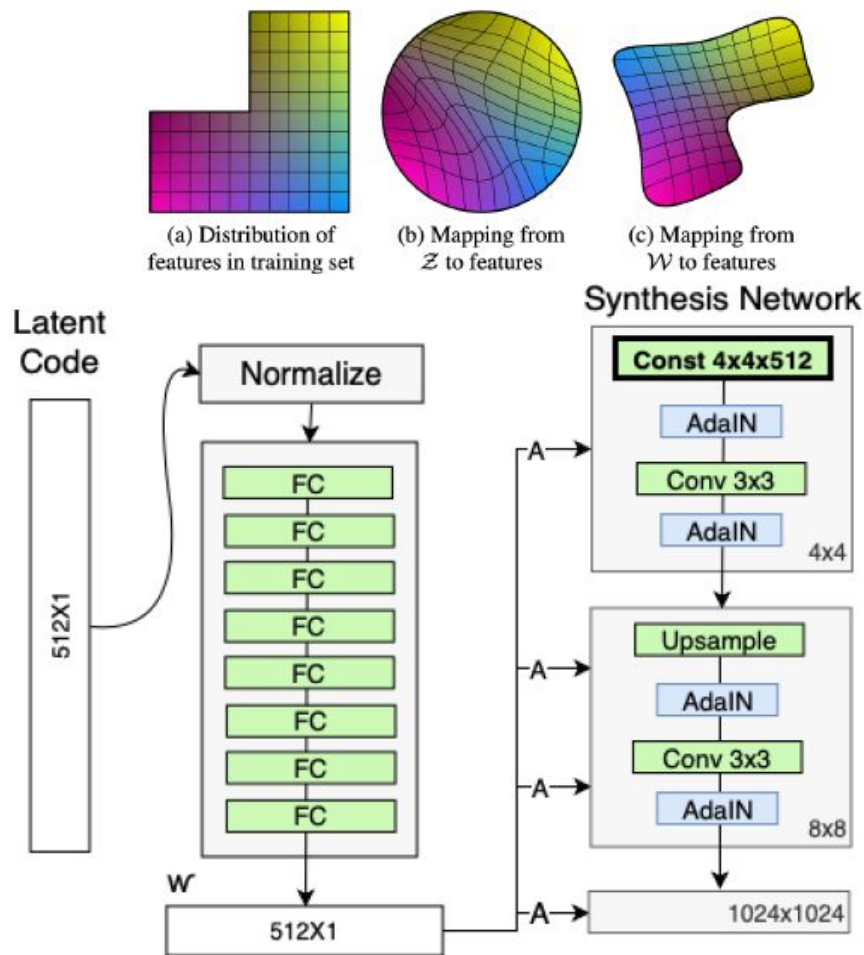
Style GAN



- ▶ Using the idea of **ProGAN** as base
- ▶ Improving Generator, keeping the same Discriminator
- ▶ Controlling specific features

StyleGAN

- ▶ Introduce a FC NN for map entangled features from input vector \mathbf{z} to latent space \mathcal{W}
- ▶ Thus, reduce correlations between components of \mathbf{z}
- ▶ Input vector \mathbf{z} is actually is a learnable constant
- ▶ At each stage (recall the [ProGAN](#)), apply apping NN to a vector, at feed it to generative model. Thus, yields a different input at a different stage.
- ▶ Inject random noise to an input at each stage to add small details and increase variety
- ▶ Adaptive Instance Normalization of each input



StyleGAN



StyleGAN2

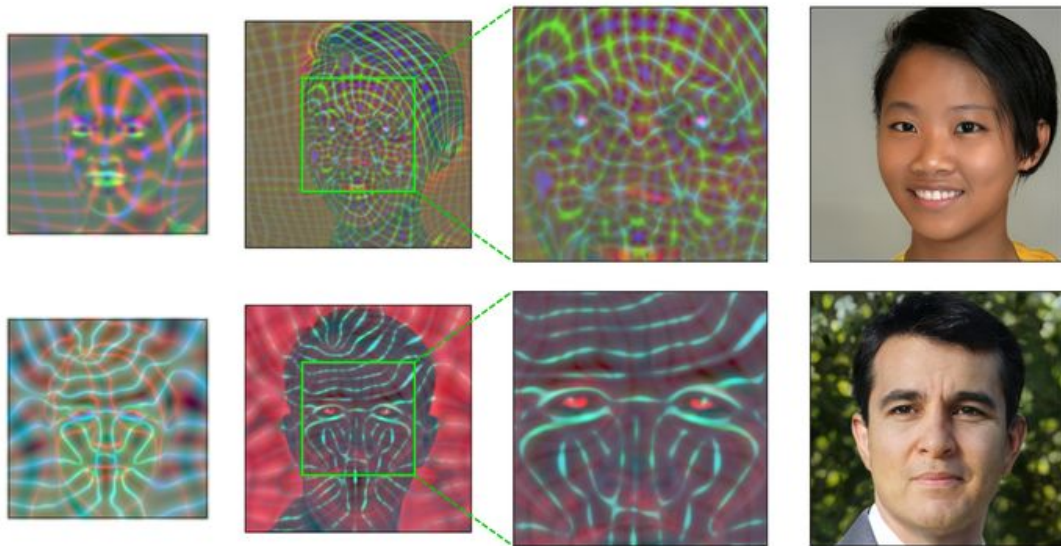
- ▶ Adaptive instance normalization allow to blend in styles at each stage effectively. Scale the input x and then force it to align channel-wise with statistics of style y

$$\text{AdaIN}(x, y) = \sigma(y) \left(\frac{x - \mu(x)}{\sigma(x)} \right) + \mu(y)$$

- ▶ But in previous work, there were little artifacts (usually at hair, teeth area). And **AdaIN** was the troublemaker. After removing it, artefacts gone completely
- ▶ This, along with few small adjustments to generator, and a few for discriminator as well, yielded a better result.

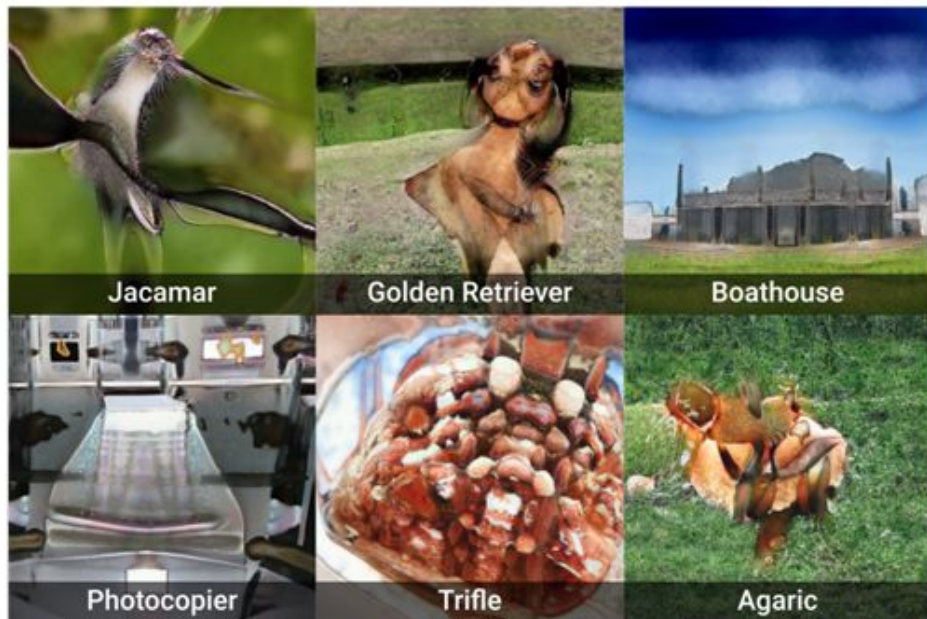
StyleGAN3

Use of fourier features, filtering, 1x1 convolution kernels and other modifications make the generator equivariant to translation and rotation



- ▶ Equivariance studies how transformations of the input image are encoded by the representation, invariance being a special case where a transformation has no effect.
- ▶ Standard convolutional architectures consist of stacked layers of operations that progressively downscale the image. Aliasing is a well-known side-effect of downsampling that may take place: it causes high-frequency components of the original signal to become indistinguishable from its low-frequency components.

StyleGAN-XL



StyleGAN3



StyleGAN-XL

StyleGAN-XL

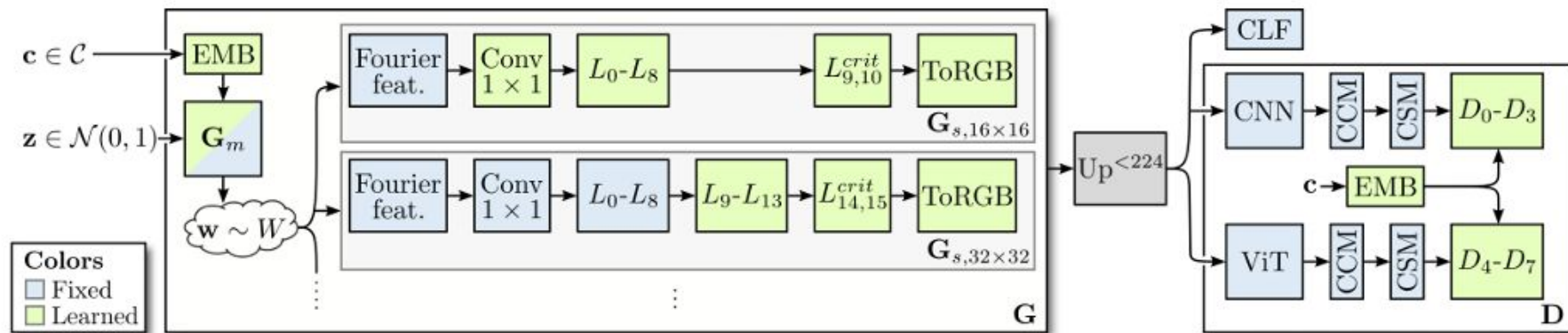
- ▶ Uses **StyleGAN3-T** and **StyleGAN3-R**, and **ProjectedGAN**:
- ▶ The original adversarial game between a generator **G** and a discriminator **D** can be extended by a set of feature projectors $\{P_l\}$. The projectors map real images x and images generated by G to the discriminator's input space. The **ProjectedGAN** objective is formulated as:

$$\min_G \max_{\{D_l\}} \sum_{l \in \mathcal{L}} \left(\mathbb{E}_x [\log D_l(P_l(x))] + \mathbb{E}_z [\log(1 - D_l(P_l(G(z))))] \right)$$

StyleGAN-XL

- ▶ Using only **StyleGAN3-T**, as **StyleGAN3-R** yield overly symmetrical images
- ▶ Spectral normalization without gradient penalties
- ▶ Blur first 200k images before feeding them to discriminator
- ▶ Reducing **StyleGAN** latent code **z** to 64
- ▶ Conditioning of labels embedding (instead of raw labels), on modified feature network
- ▶ Using generalized embedding for a class from **EfficientNet** and **ViT** before applying to discriminator
 - ▶ Using **DeiT-small** as a classifier, add cross-entropy to generator loss

StyleGAN-XL



- ▶ Labels c and code z forwarded to a feature mapping net (recall vanilla StyleGAN)
- ▶ Train a several generators G (as in ProGAN and in StyleGAN)
- ▶ Upsample, if necessary (should be larger then 224×224)
- ▶ Forward output to ViT and CCN model before applying discriminator stage

<https://arxiv.org/pdf/2202.00273v2.pdf>