On Generative Models

CS189/289A: Introduction to Machine Learning

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Outline

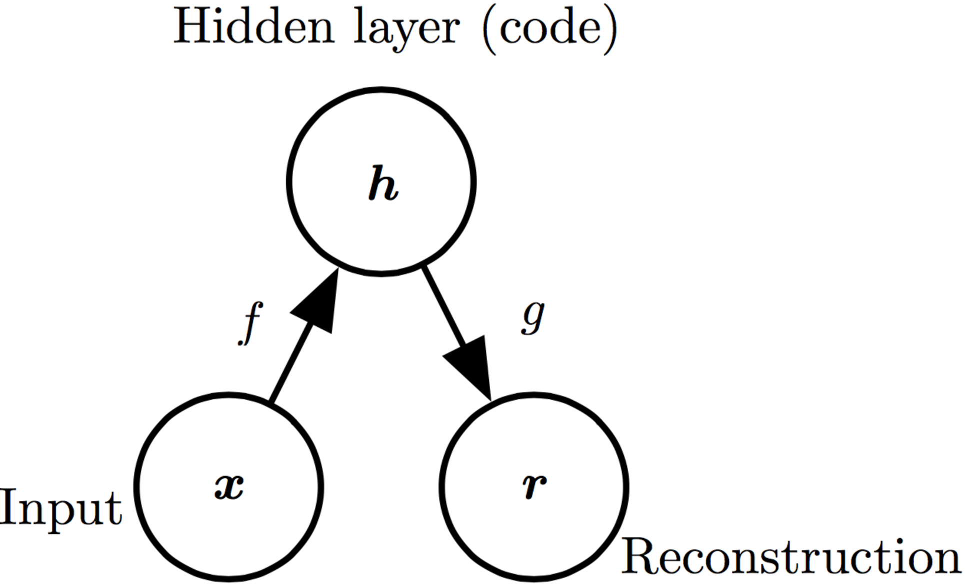
1. Why generative models
2. Autoencoder (AE)
3. Variational Autoencoder (VAE)
4. Generative Adversarial Networks (GAN)

Why Generative Models

1. More of the kind:

2. *What I cannot create, I do not understand.* – Richard Feynman

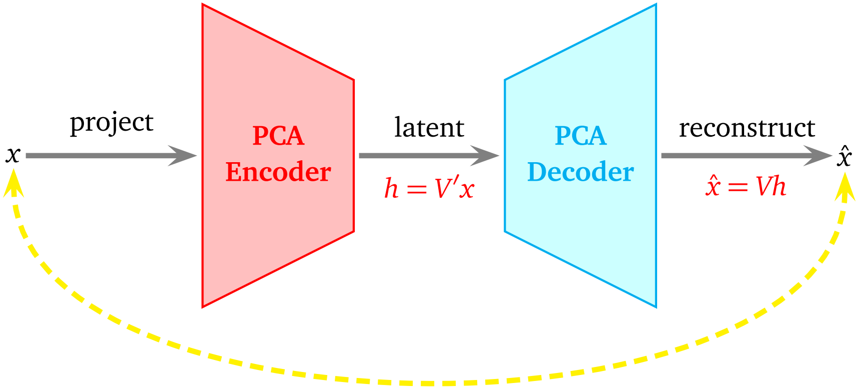
Autoencoder (AE)



Avoiding Trivial Identity

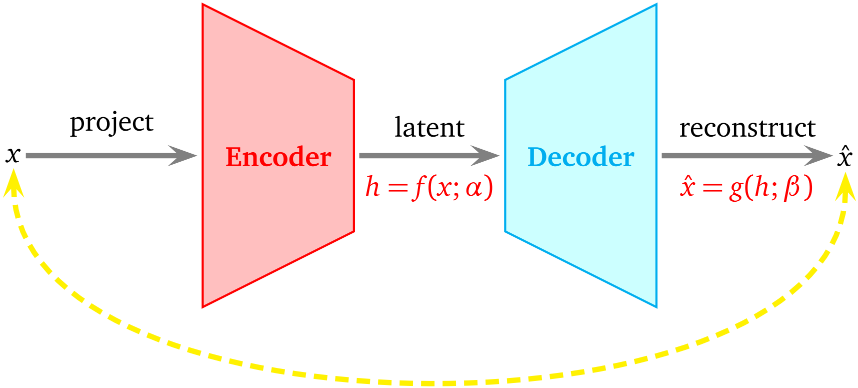
1. Undercomplete autoencoders
   - h has lower dimension than x
   - f or g has low capacity (e.g., linear g)
   - Must discard some information in h
2. Overcomplete autoencoders
   - h has higher dimension than x
   - Must be regularized: e.g. sparsity

PCA as An Encoder-Decoder Pipeine



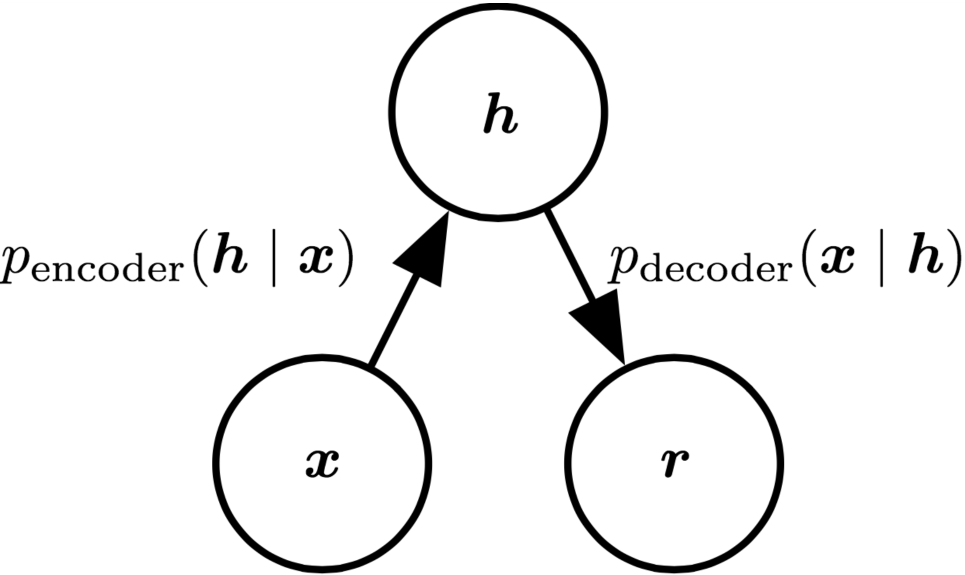
$$\min \quad \text{loss}(\hat{x}, x) = E[\|x - \hat{x}\|^2]$$

AE: A Nonlinear Encoder-Decoder Pipeine



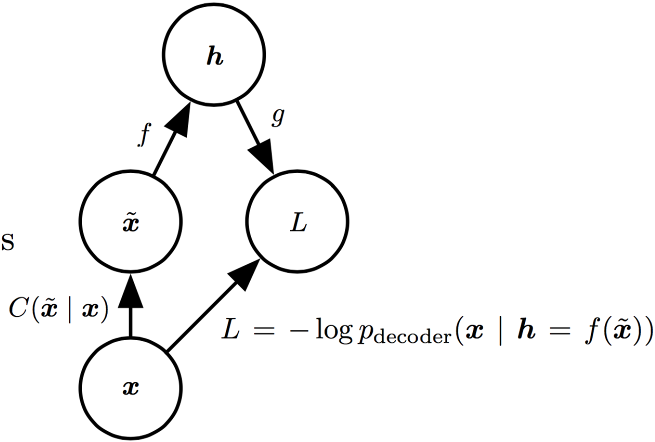
$$\min \quad \text{loss}(\hat{x}, x) = E[\|x - \hat{x}\|^2]$$

Stochastic Autoencoder

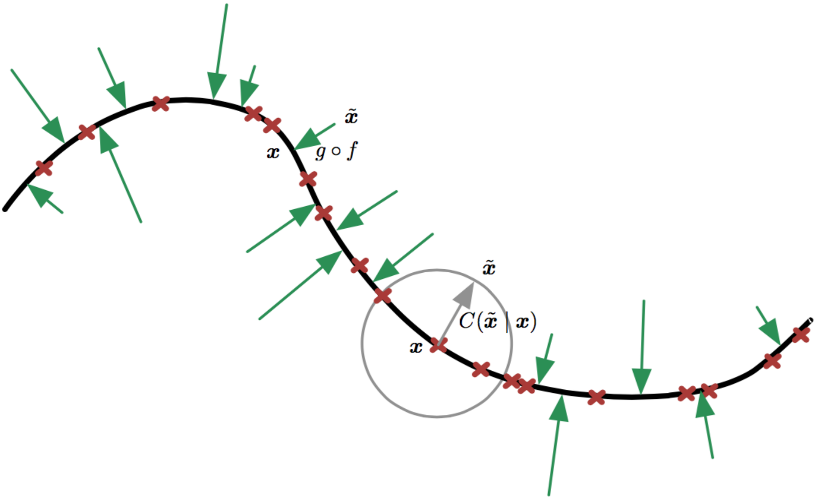


Denoising Autoencoder

C: corruption process
(introduce noise)



Denoising Autoencoder Learns A Manifold



Generative Model: Overall Approach

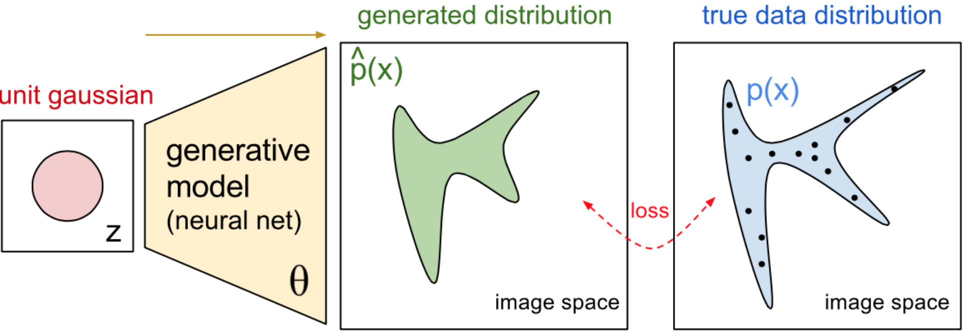
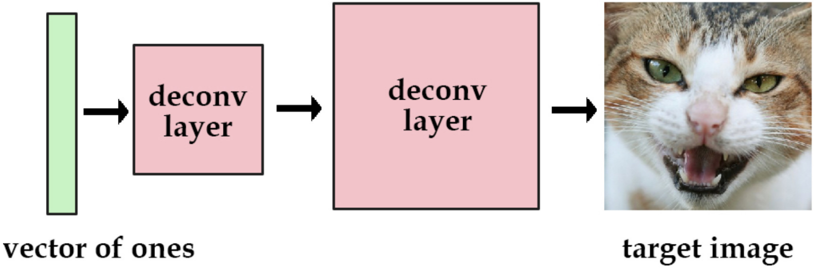
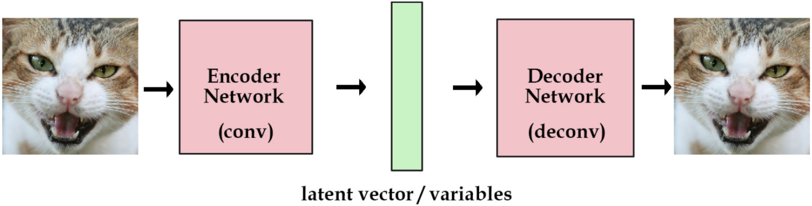


Image Generator Given A Code

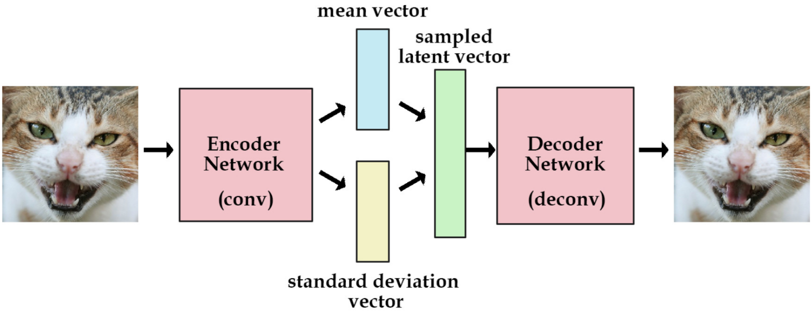


Variational Autoencoders Explained, Kevin Frans, 2016

An Autoencoder Learns Latent Code



VAE Captures and Models Code Distribution



VAE Sample Results

left: 1st epoch, middle: 9th epoch, right: original

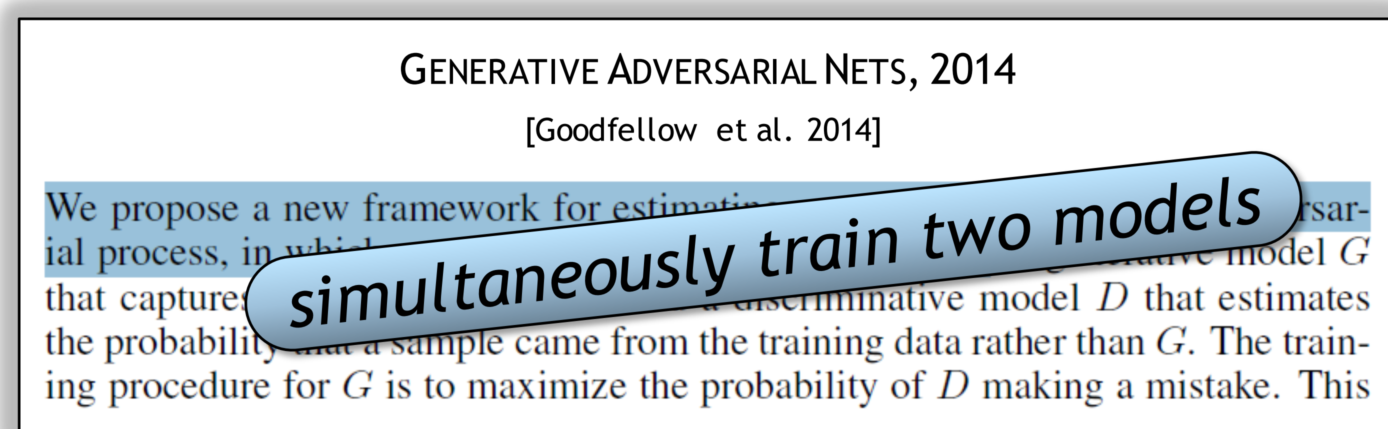
Progressive Growing of GANs for Improved Quality, Stability, and Variation

Tero Karras NVIDIA
Timo Aila NVIDIA
Samuli Laine NVIDIA
Jaakko Lehtinen NVIDIA and Aalto University
{tkarras,taila,slaine,jlehtinen}@nvidia.com

Abstract

We describe a new training methodology for generative adversarial networks. The key idea is to grow both the generator and discriminator progressively: starting from a low resolution, we add new layers that model increasingly fine details as training progresses. This both speeds the training up and greatly stabilizes it, allowing us to produce images of unprecedented quality, e.g., CelebA images at 1024^2. We also propose a simple way to increase the variation in generated images, and achieve a record inception score of 8.80 in unsupervised CIFAR10. Additionally, we describe several implementation details that are important for discouraging unhealthy competition between the generator and discriminator. Finally, we suggest a new metric for evaluating GAN results, both in terms of image quality and variation. As an additional contribution, we construct a higher-quality version of the CelebA dataset.

Generative Adversarial Networks (GAN)



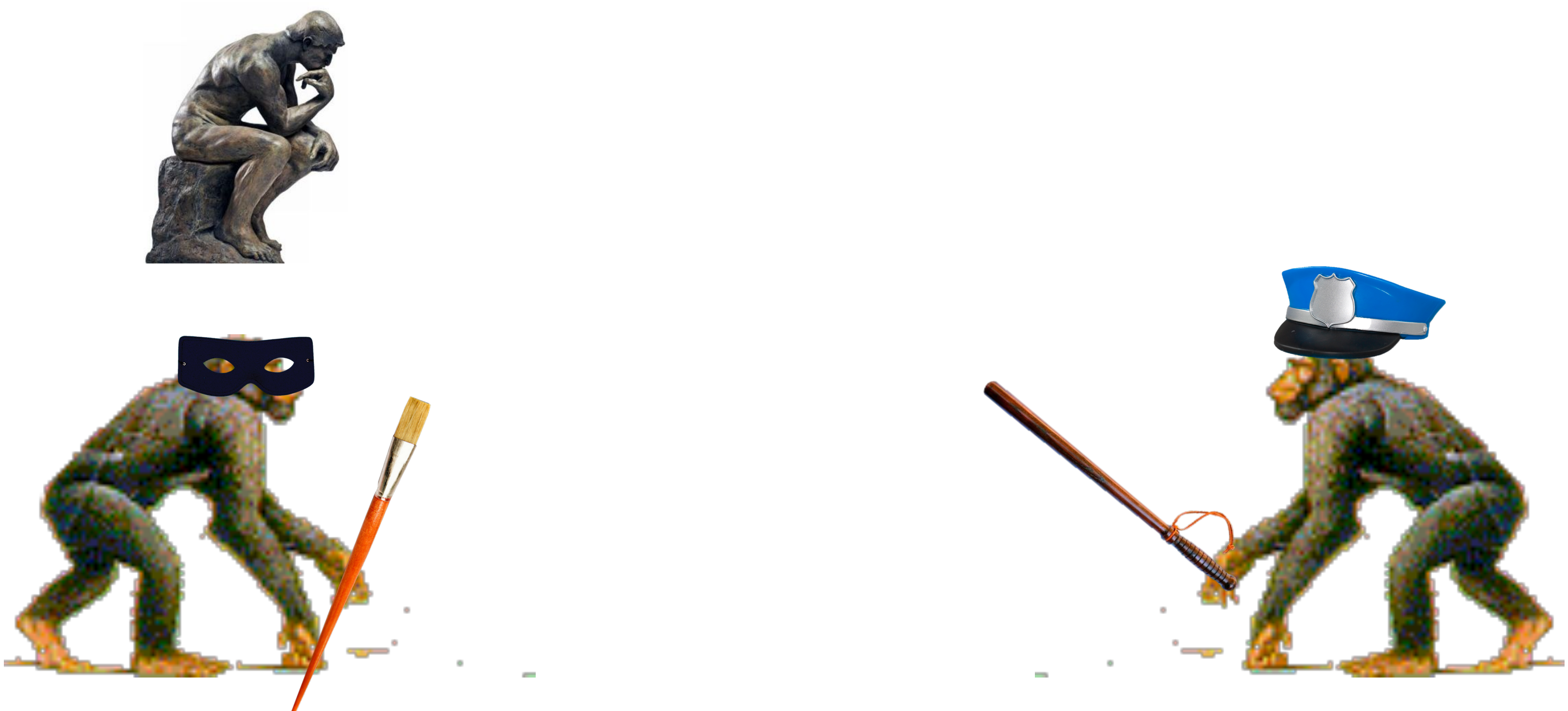
Acknowledgements: The following set of slides are provided by Tero Karras and Jaakko Lehtinen.

Player 1

Player 2


Fake!
Player 1
Player 2


Fake!
Player 1
Player 2



Player 1

Player 2

Player 1

Player 2

Player 1

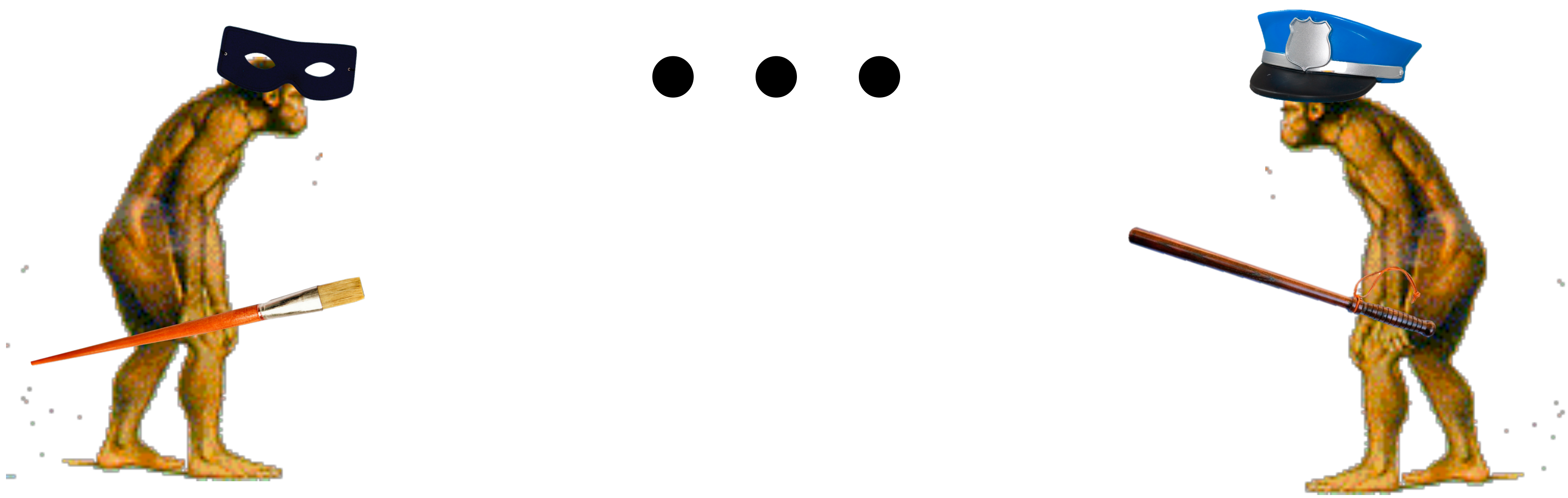
Player 2

Player 1

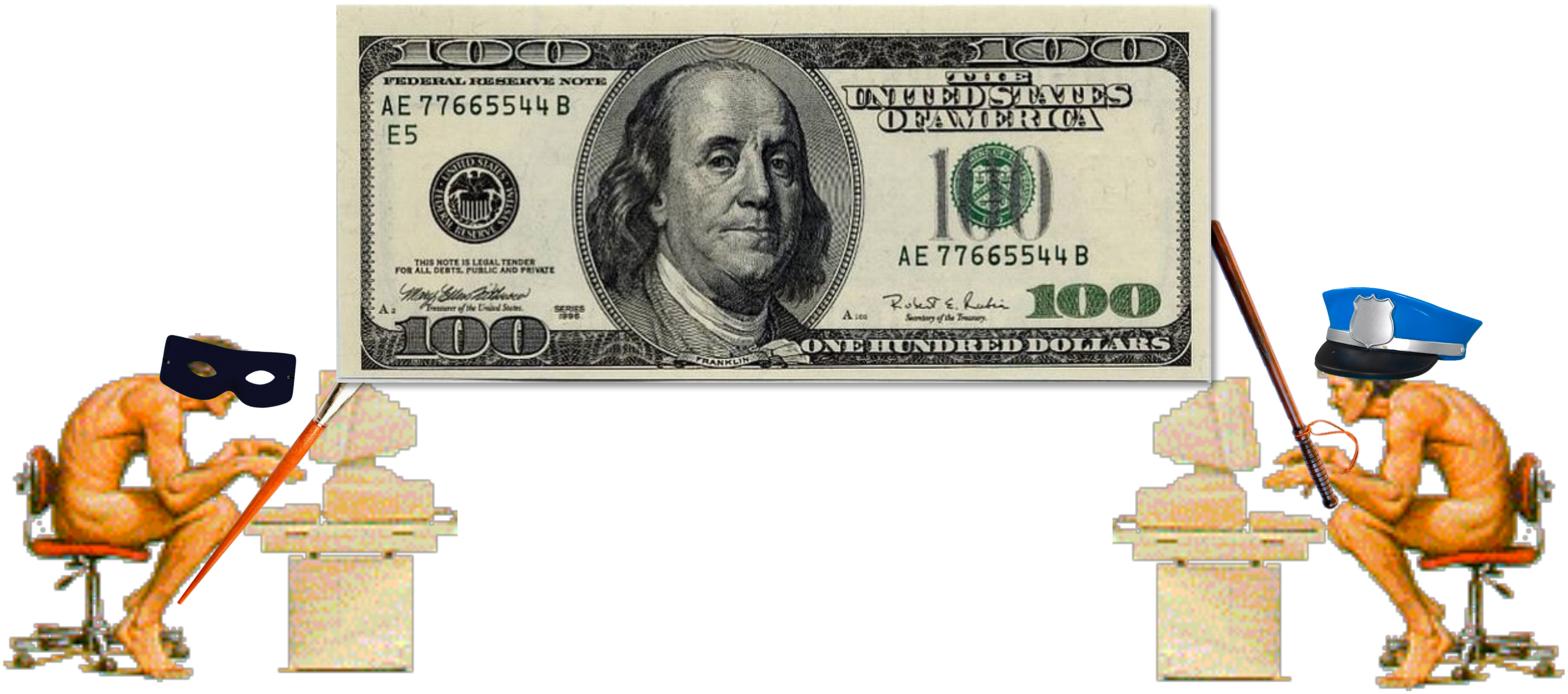
Player 2

Player 1

Player 2



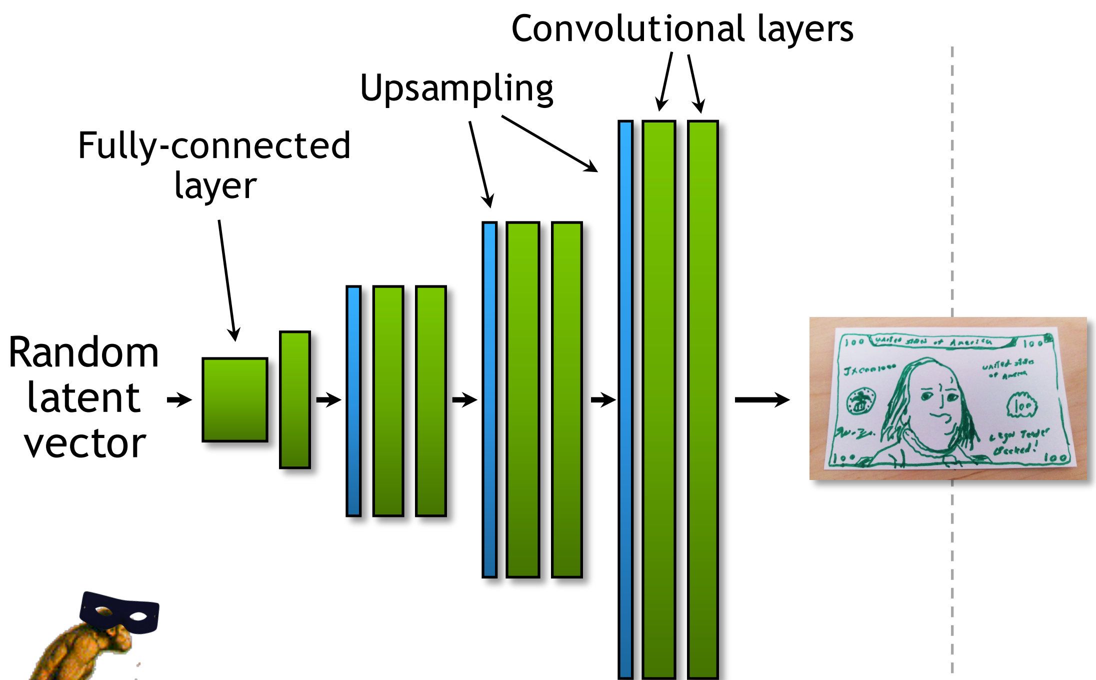
Player 1　　　　　　　　　　　　　　　　　　　　Player 2



Player 1

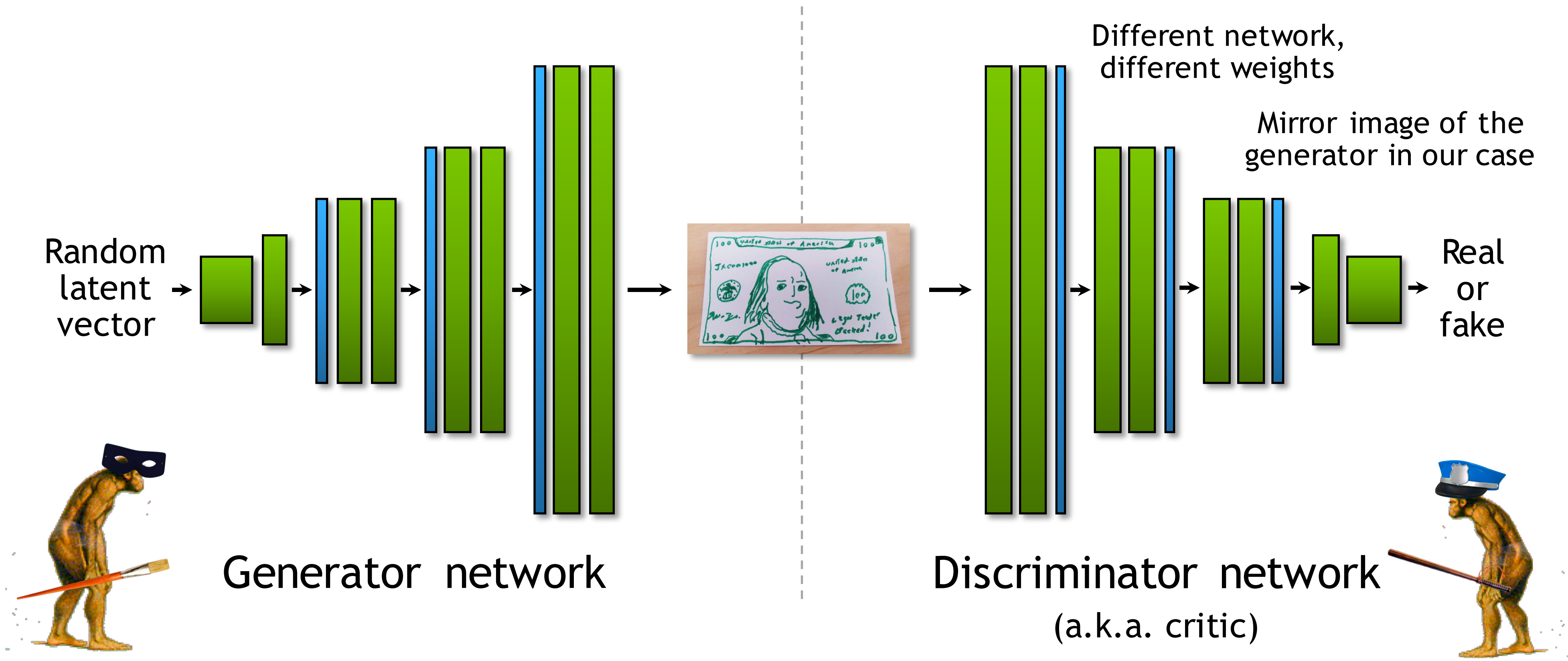
Player 2

In practice

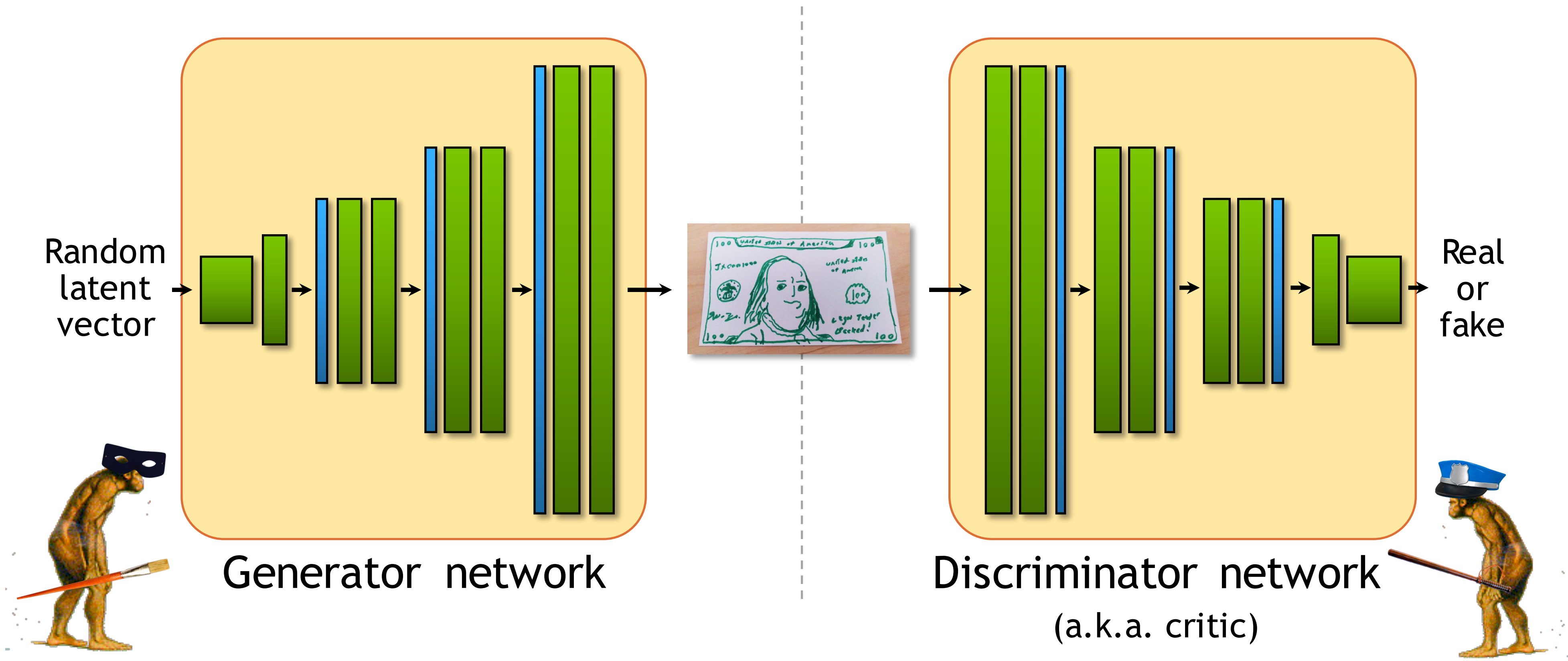


Generator network

In practice


Random latent vector
Different network, different weights
Mirror image of the generator in our case
Real or fake
Generator network
Discriminator network
(a.k.a. critic)

Training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Generator network
Discriminator network
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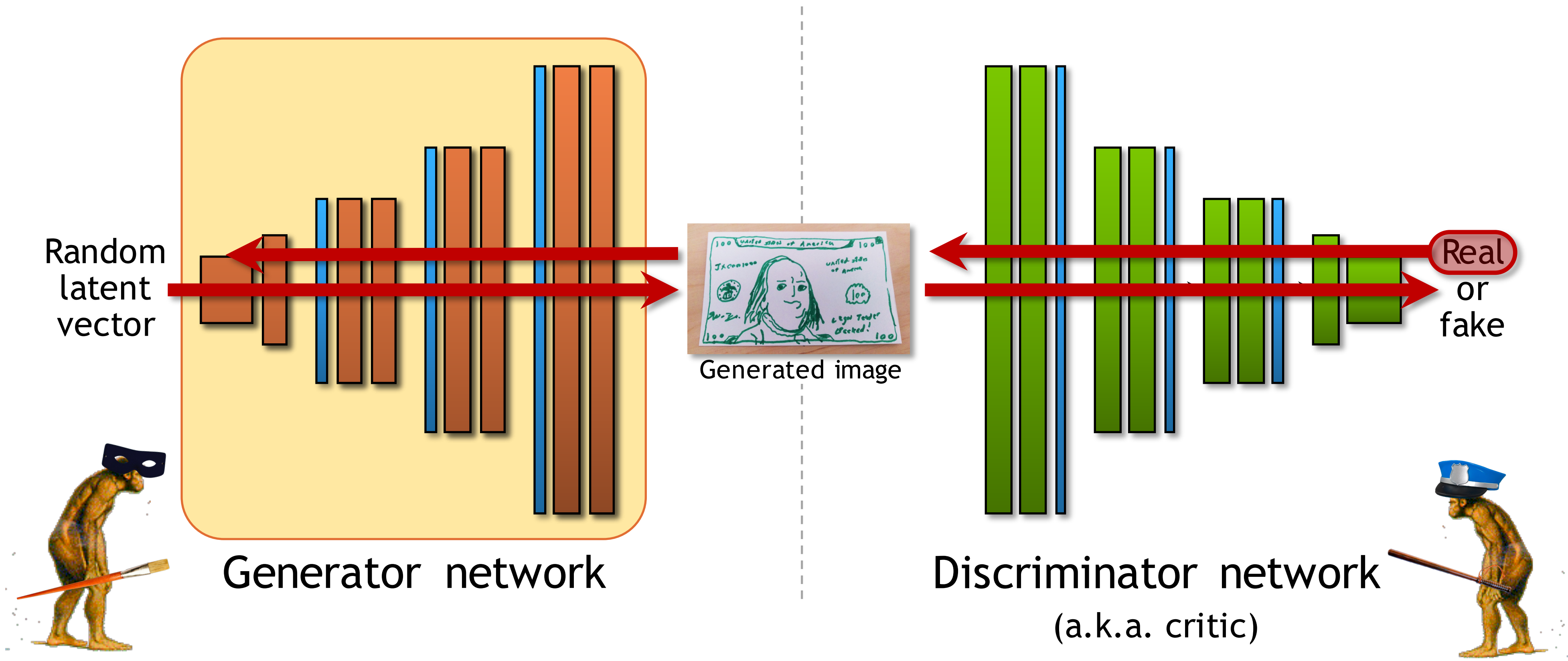
Real or fake

Training


Random
latent
vector
Generated image
Real
or
fake
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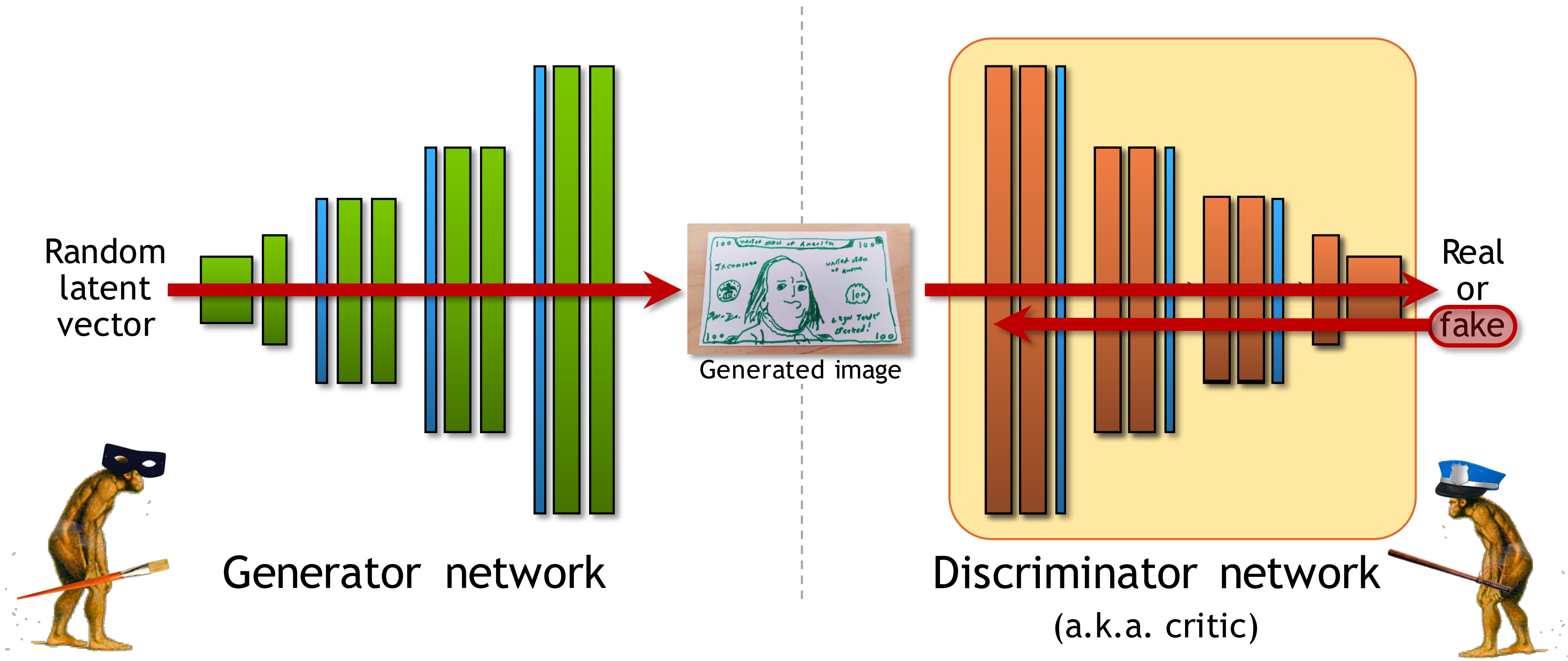
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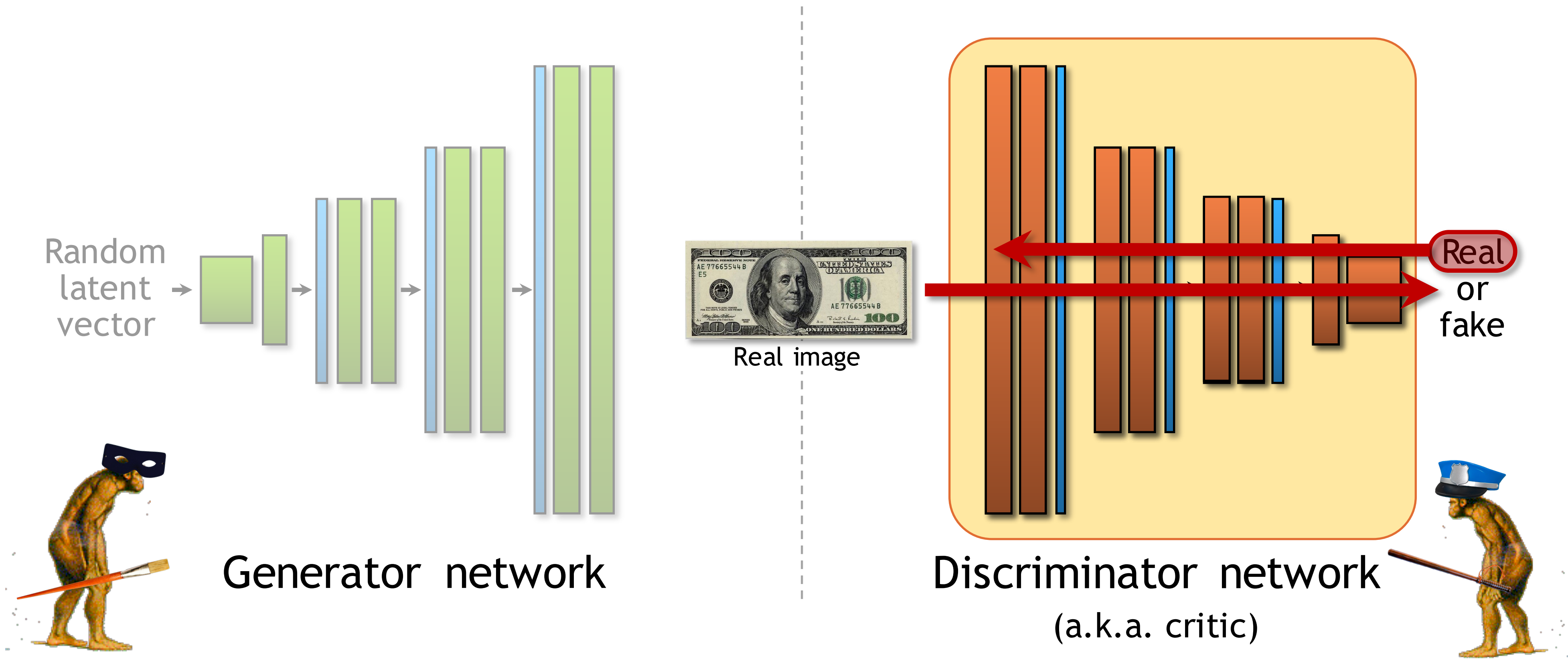
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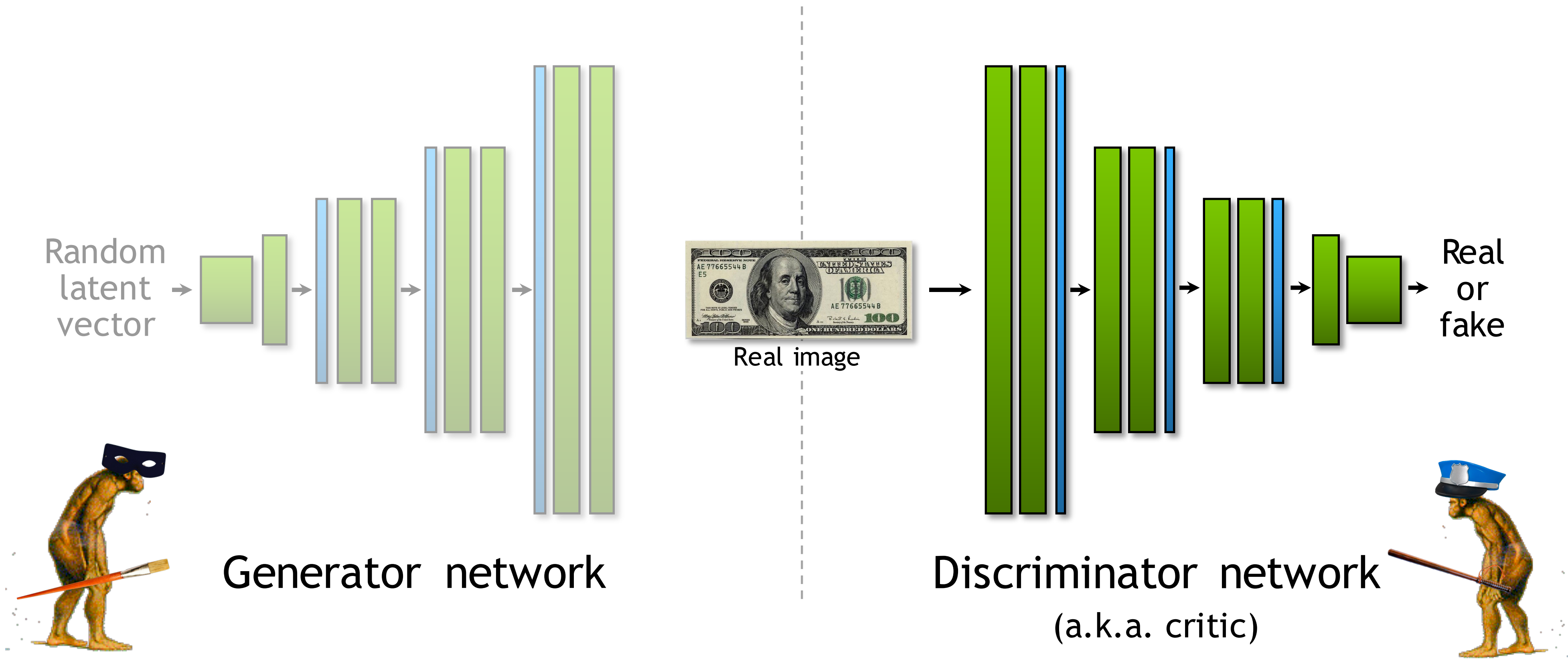
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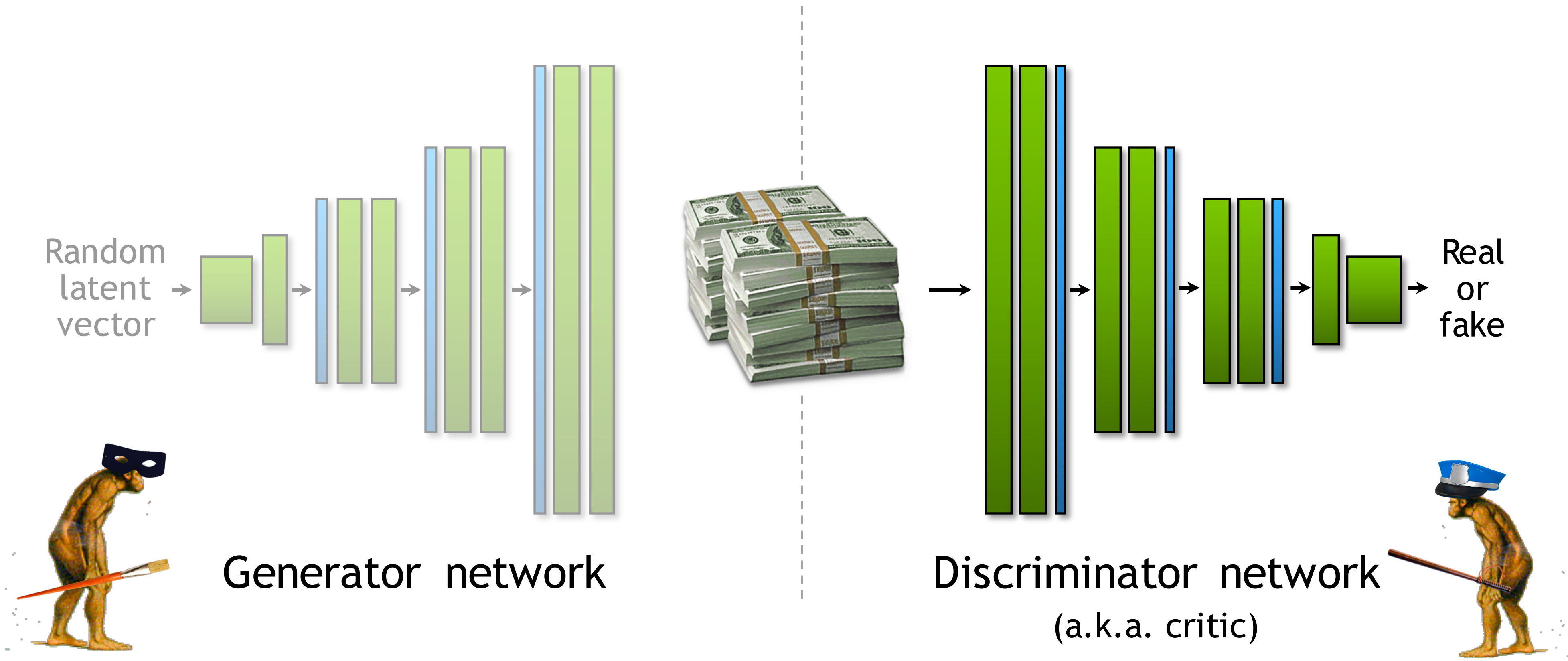
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Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks, 2016

good image representations is by training Generative Adversarial Networks (GANs) (Goodfellow et al., 2014), and later reusing parts ... criminator networks as feature extractors for supervised tasks. GANs pr ... ive to maximum likelihood techniques. One can additionally argue that th ... process and the lack of a heuristic cost function (such as pixel-wise independent mean-square error) are attractive to representation learning. GANs have

attractive

Towards Principled Methods for Training Generative Adversarial Networks, 2017

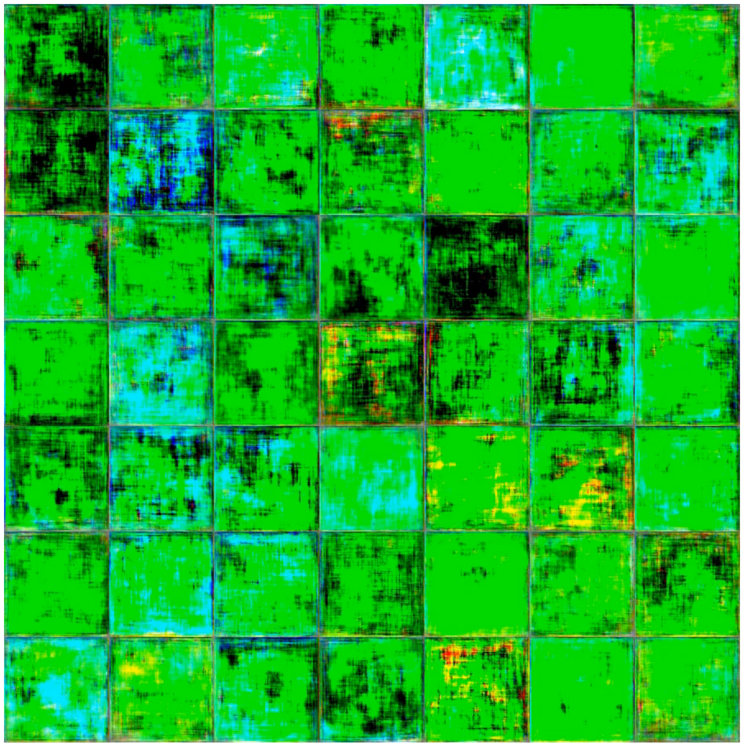
great success

Gen ... networks (GANs)(Goodfellow et al., 2014a) have achiev... gene ... ages. However, they are widely ... starting to be app... ortant problems, ... abi-lizing sequence learning methods for speech and language, ... et al., 2015; Radford et al., 2015; Salimans et al., 2016; Lamb et al., 2016; Wu et al., 2016)

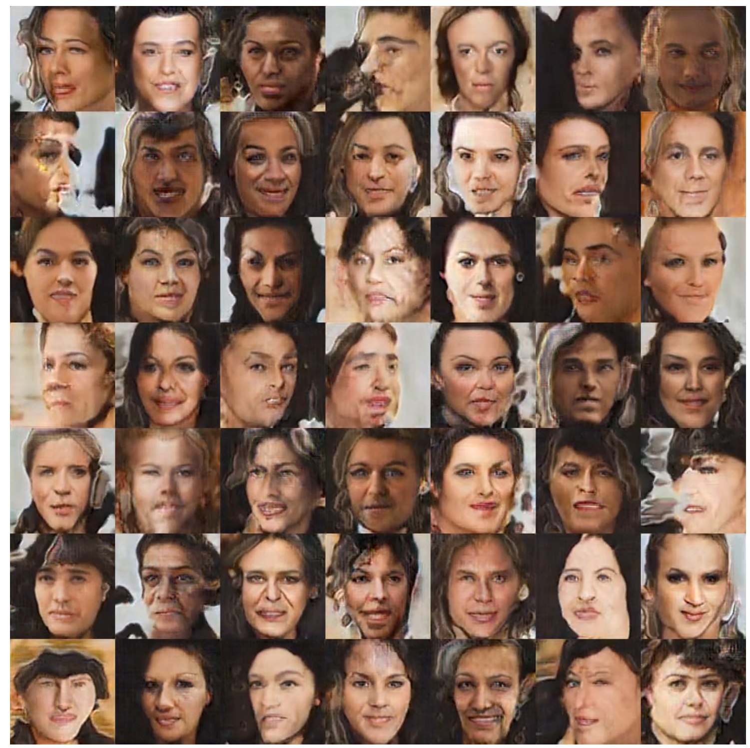
realistic images

widely general

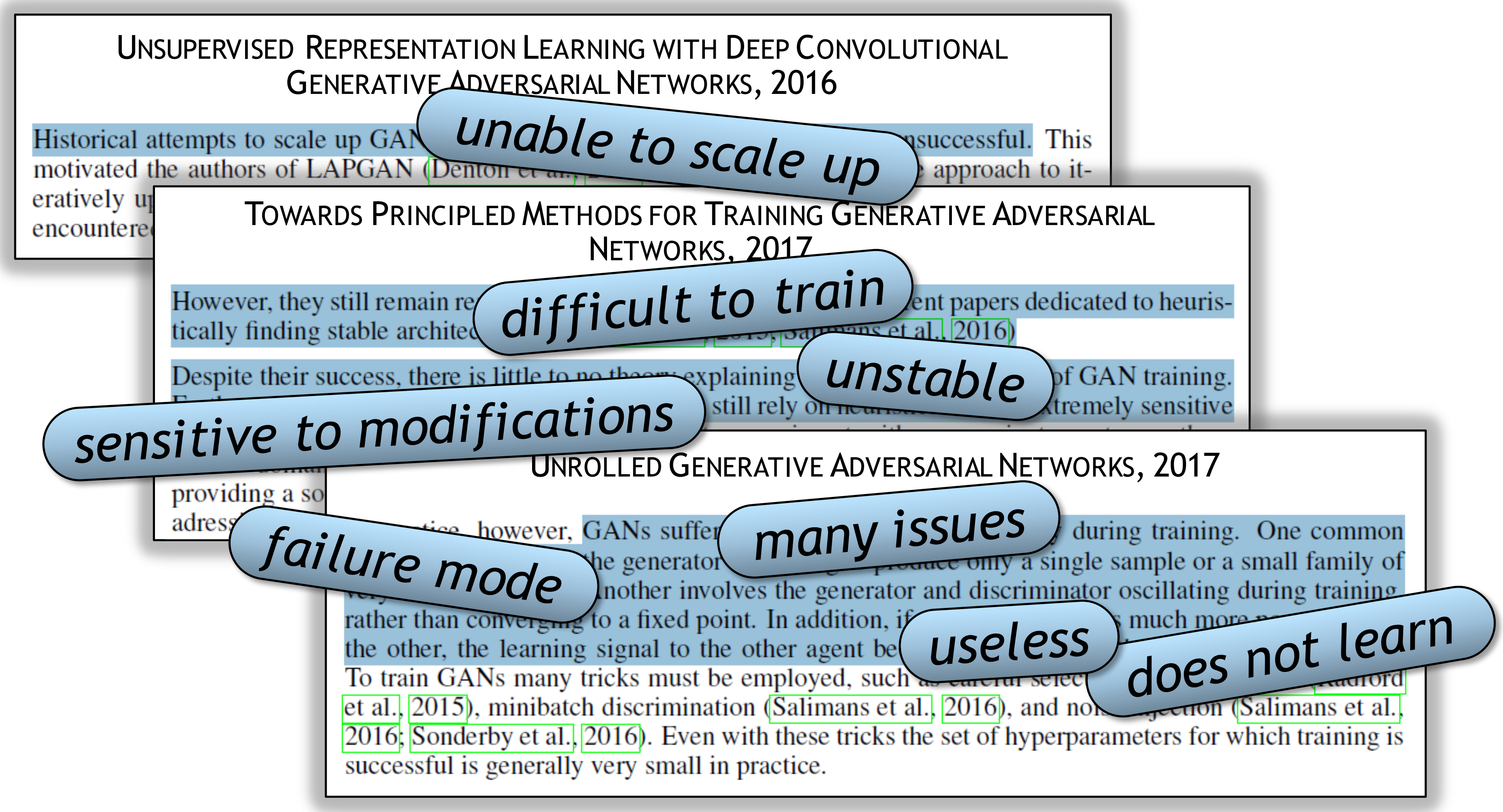
What could possibly go wrong?



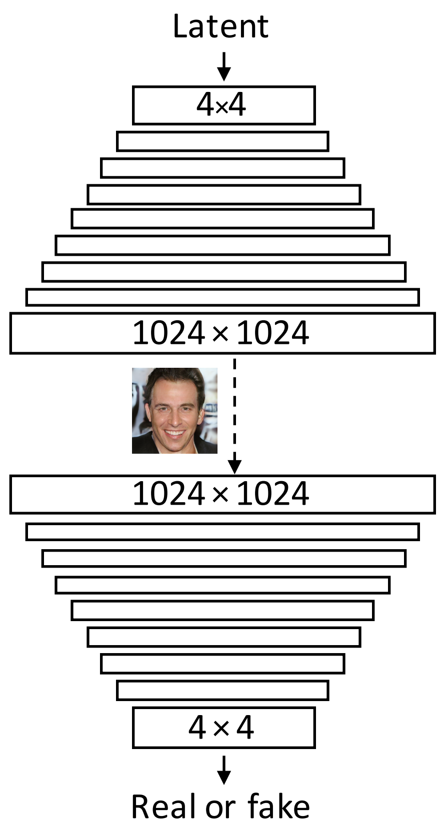
What could possibly go wrong?



What could possibly go wrong?

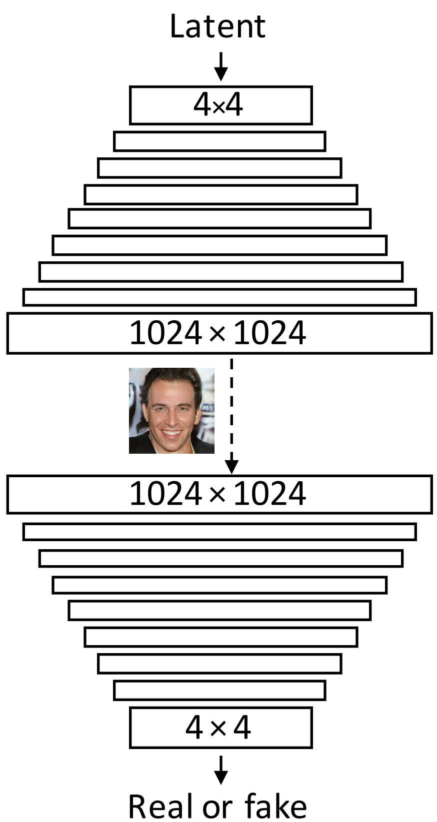

UNSUPERVISED REPRESENTATION LEARNING WITH DEEP CONVOLUTIONAL GENERATIVE ADVERSARIAL NETWORKS, 2016
TOWARDS PRINCIPLED METHODS FOR TRAINING GENERATIVE ADVERSARIAL NETWORKS, 2017
UNROLLED GENERATIVE ADVERSARIAL NETWORKS, 2017
unable to scale up
difficult to train
unstable
sensitive to modifications
many issues
failure mode
useless
does not learn
To train GANs many tricks must be employed, such
et al., 2015), minibatch discrimination (Salimans et al., 2016), and no
2016; Sonderby et al., 2016). Even with these tricks the set of hyperparameters for which training is
successful is generally very small in practice.

Traditional approach

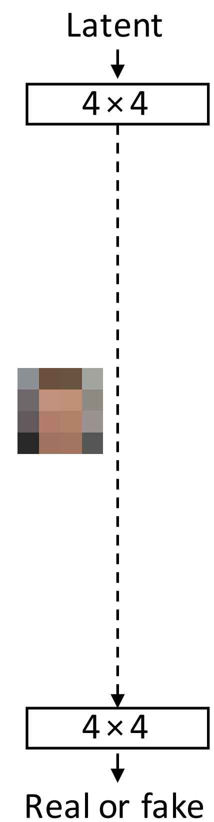


- High resolution ⇒ deep networks
- All layers are initialized to random weights
- Neither of the two networks has any idea what it's supposed to do!

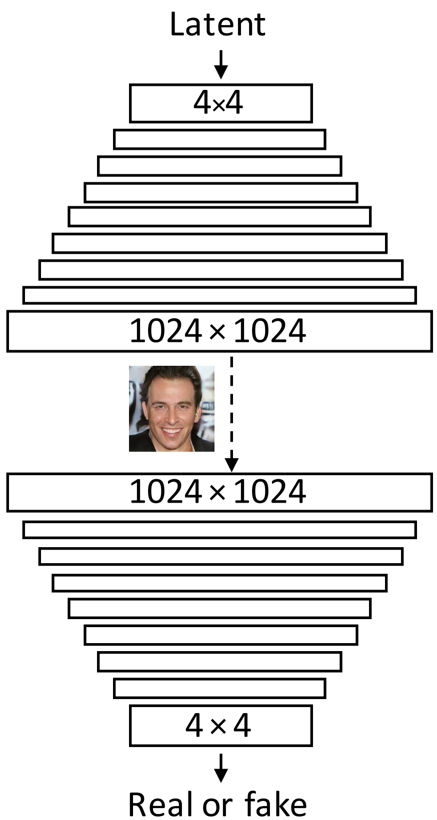
Traditional approach



Progressive growing



Traditional approach



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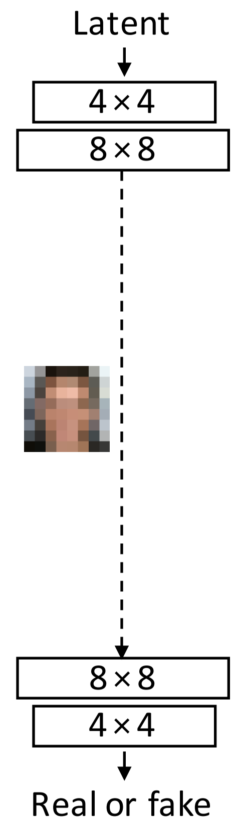

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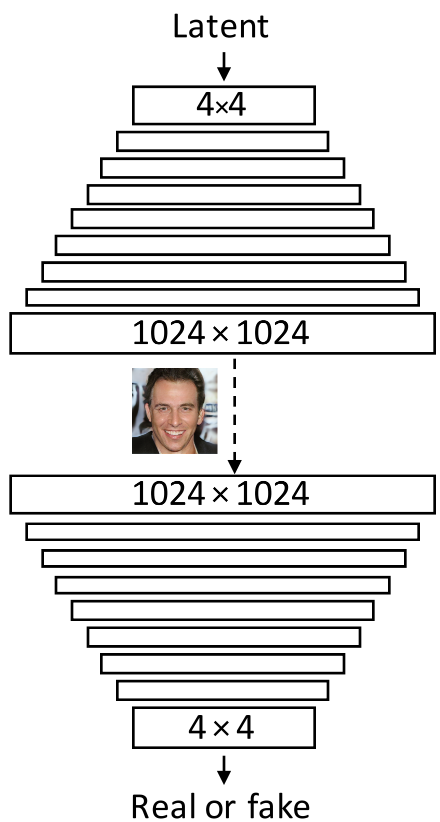

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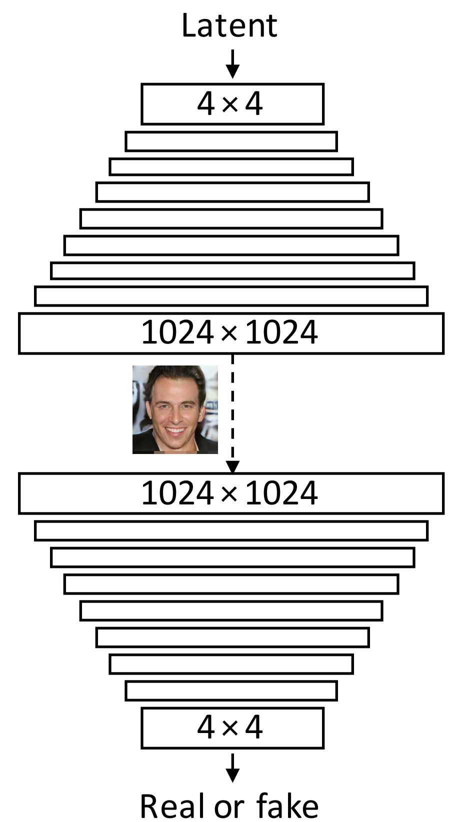

Figure 5: 1024×1024 images generated using the CELEBA-HQ dataset. See Appendix F for a larger set of results, and the accompanying video for latent space interpolations. On the right, two images from an earlier megapixel GAN by Marchesi (2017) show limited detail and variation.