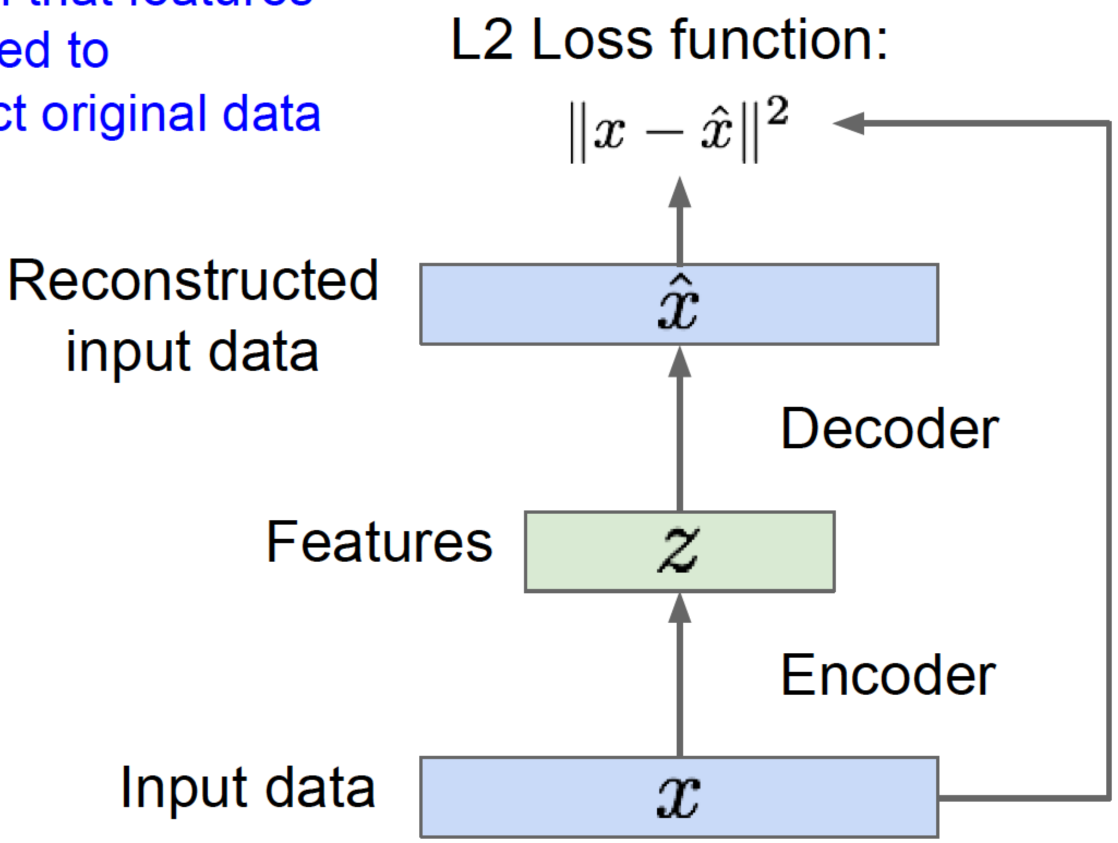
Generative Adversarial Networks (GANs)

Bindita Chaudhuri

Unsupervised Learning: Autoencoders

Train such that features can be used to reconstruct original data



Unsupervised Learning: Autoencoders

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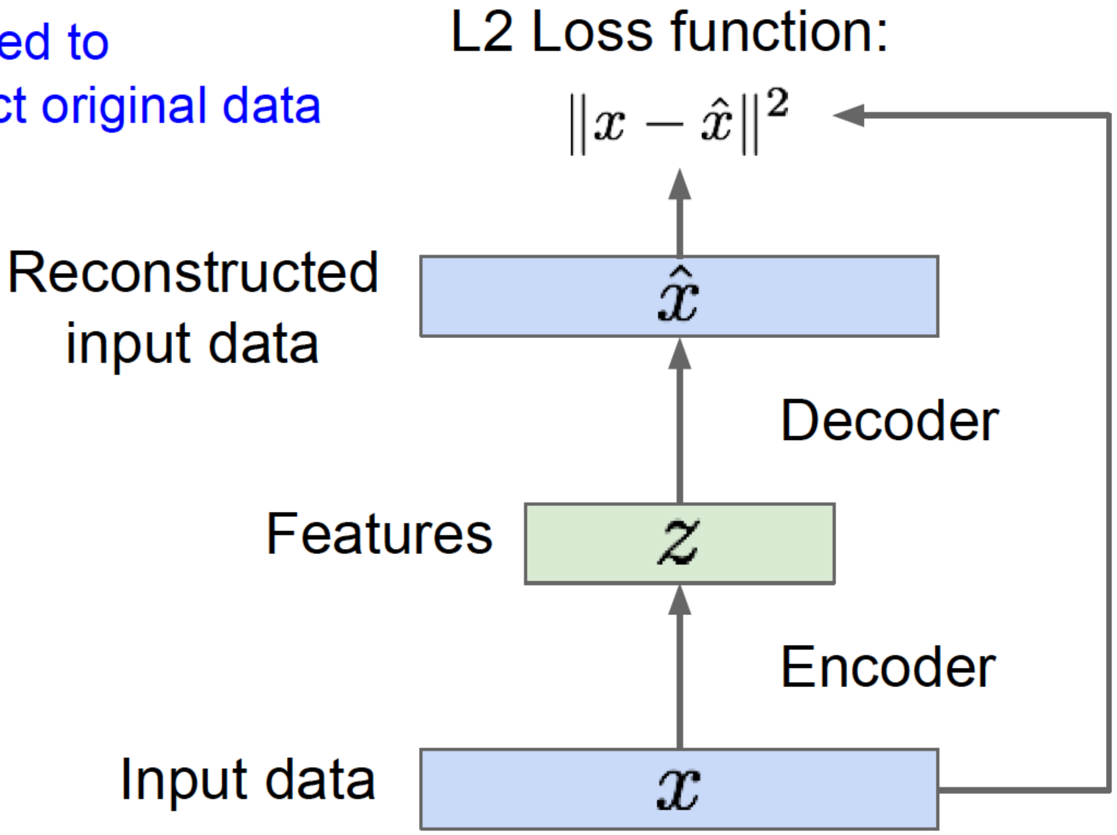
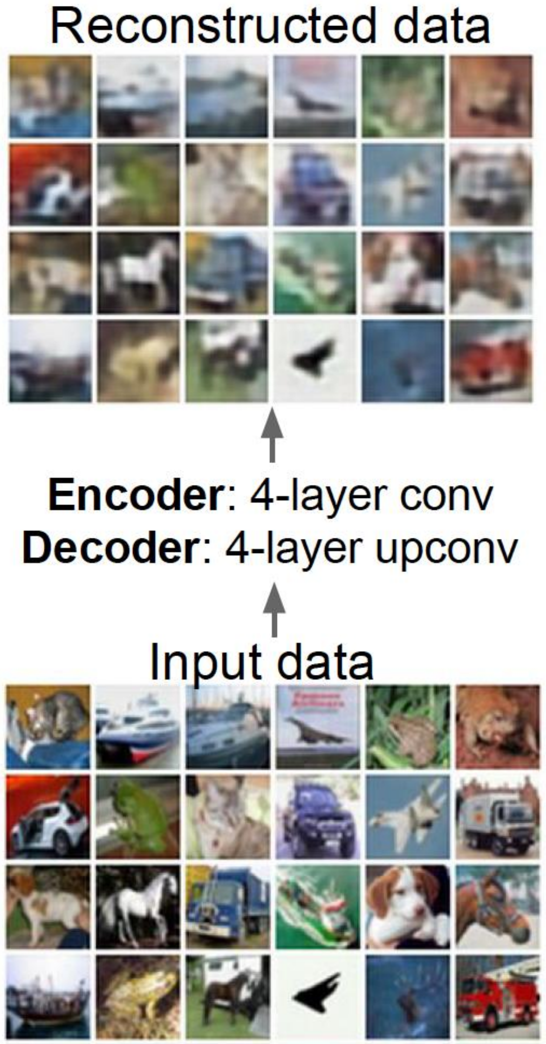
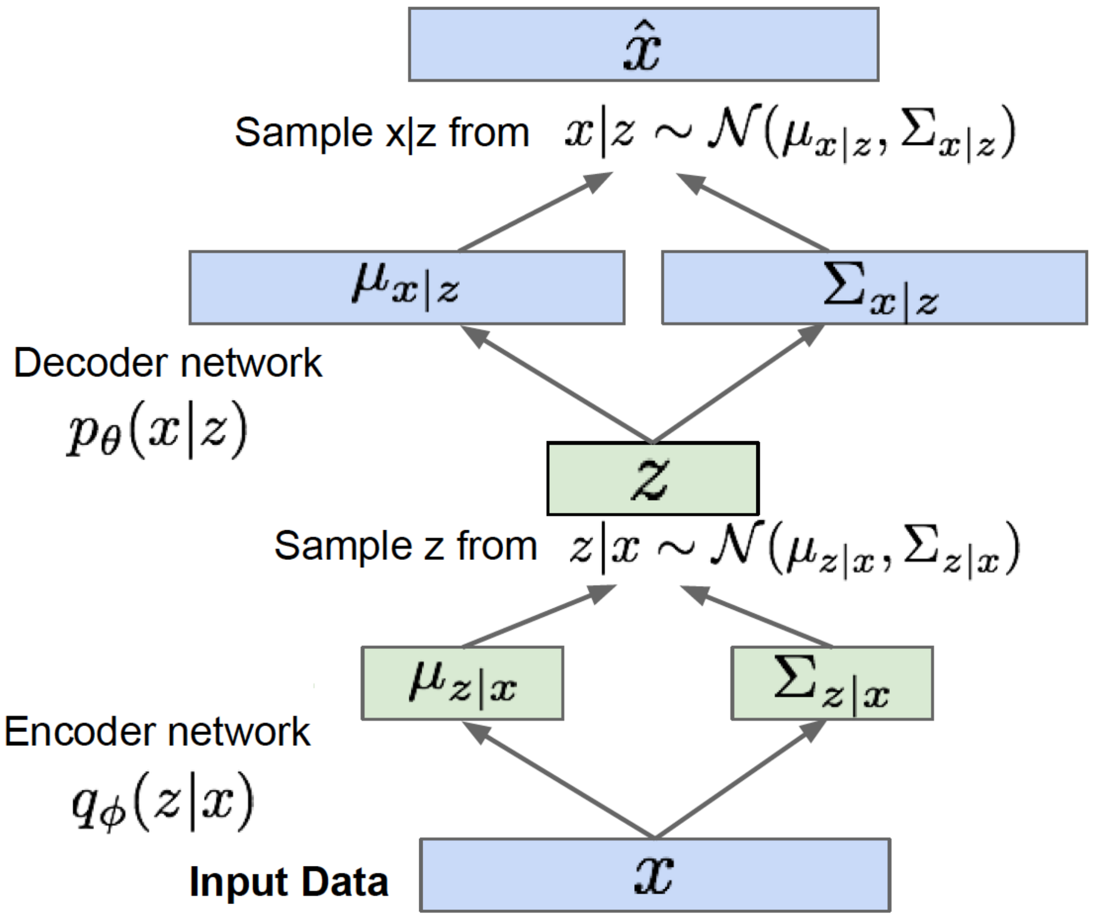
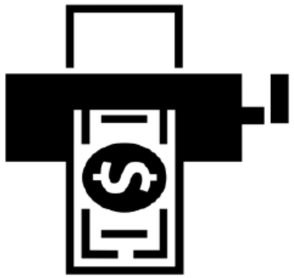




Unsupervised Learning: Variational Autoencoders

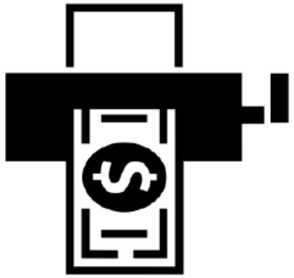


Generative Adversarial Networks: Idea



Generator (Counterfeiter): Creates fake data from random input

Generative Adversarial Networks: Idea



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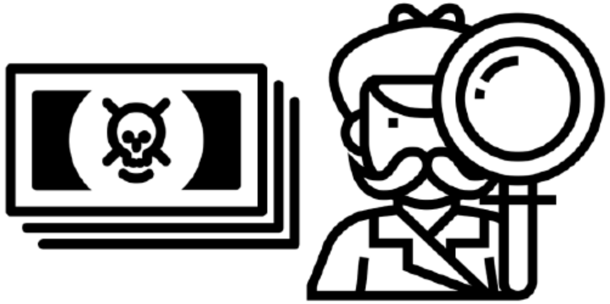
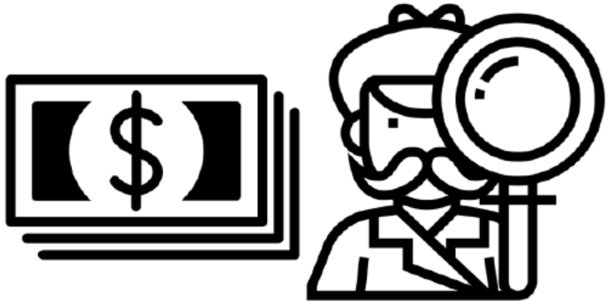


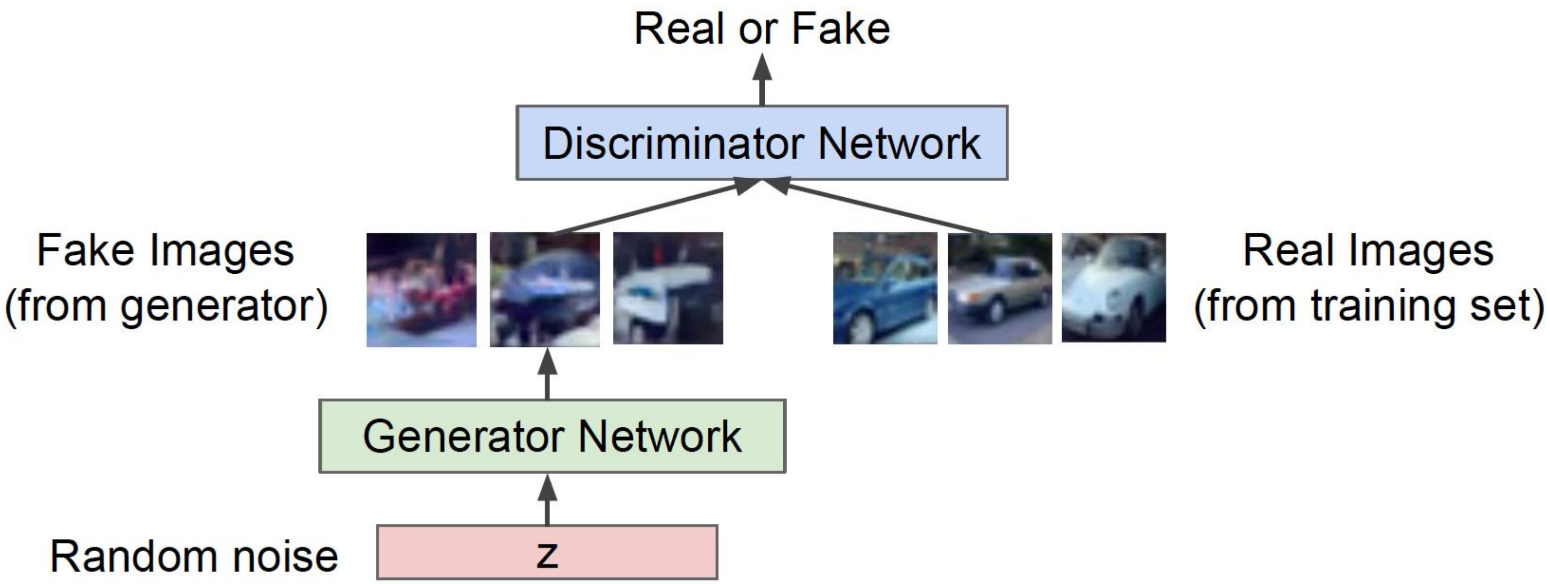
→ Looks Fake!

Discriminator (Detective): Distinguish real data from fake data

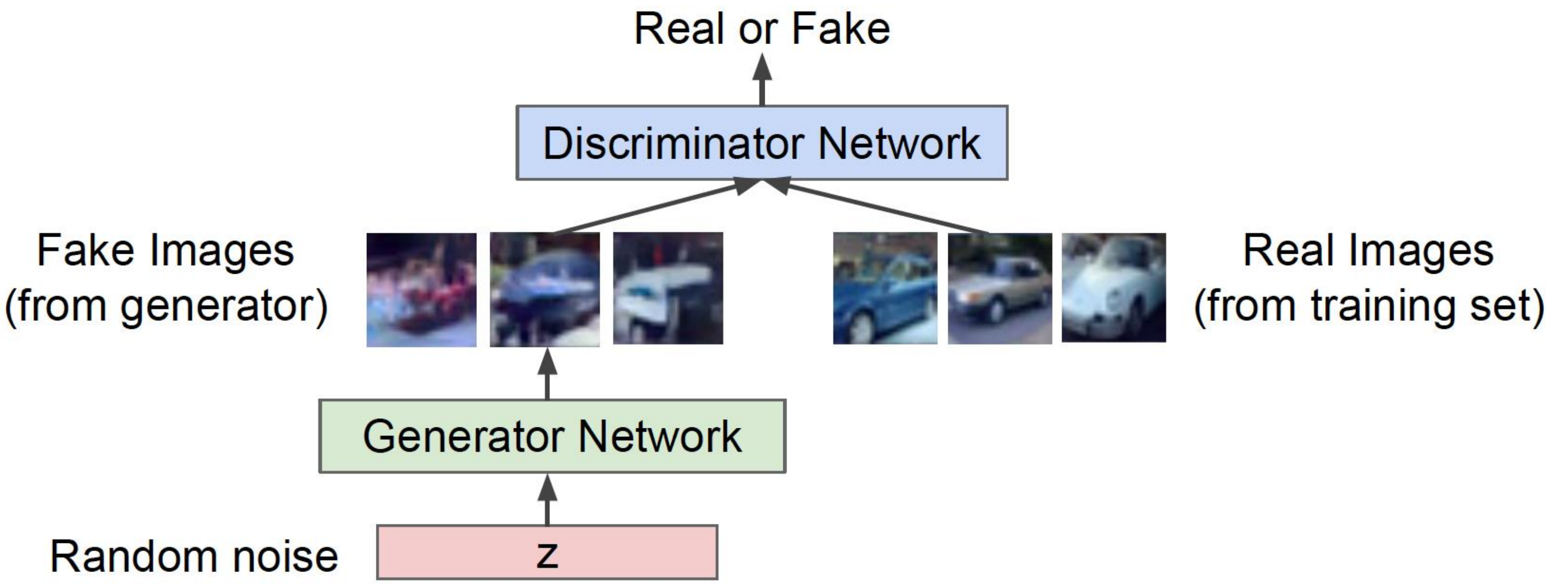


→ Looks Real!

Generative Adversarial Networks



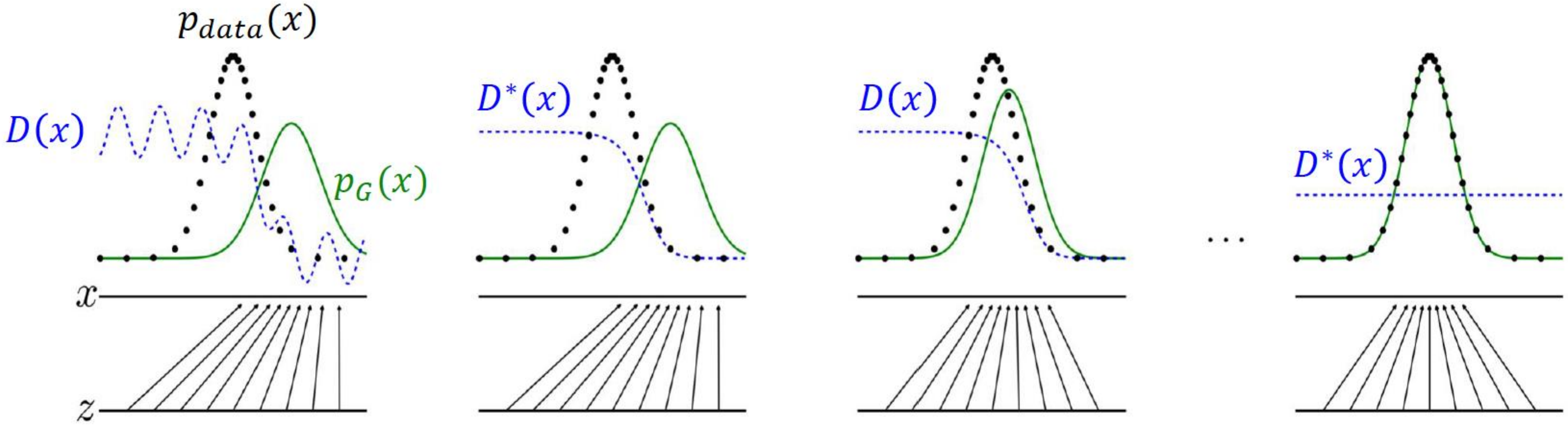
Generative Adversarial Networks



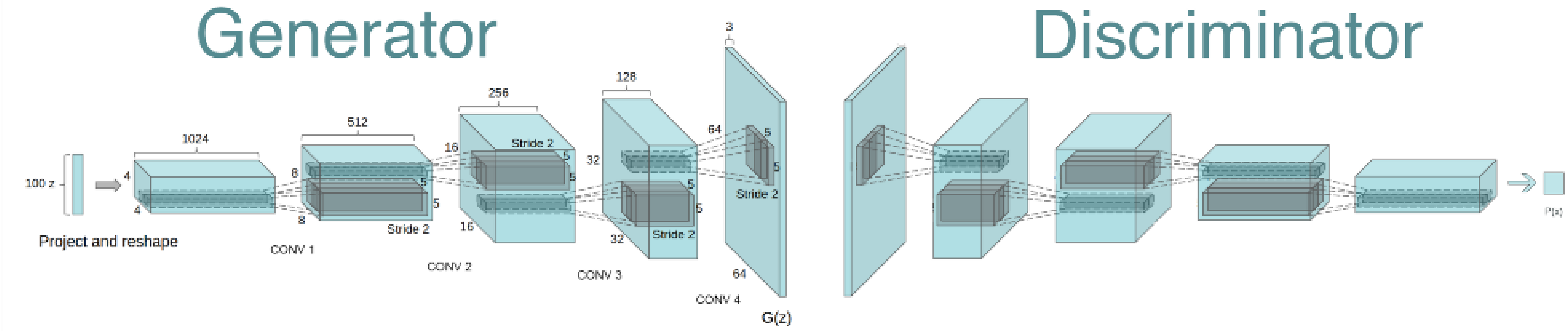
Minimax objective function:

$$\min_{\theta_g} \max_{\theta_d} \left[\mathbb{E}_{x \sim p_{data}} \log \underbrace{D_{\theta_d}(x)}_{\text{Discriminator output for real data x}} + \mathbb{E}_{z \sim p(z)} \log(1 - \underbrace{D_{\theta_d}(G_{\theta_g}(z))}_{\text{Discriminator output for generated fake data G(z)}}) \right]$$

Distributions during training



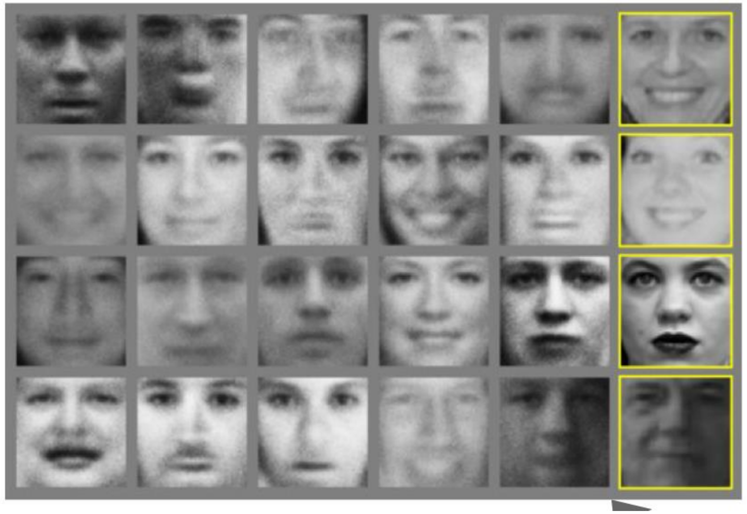
GAN: Sample Architecture (DC-GAN)



Generated Samples

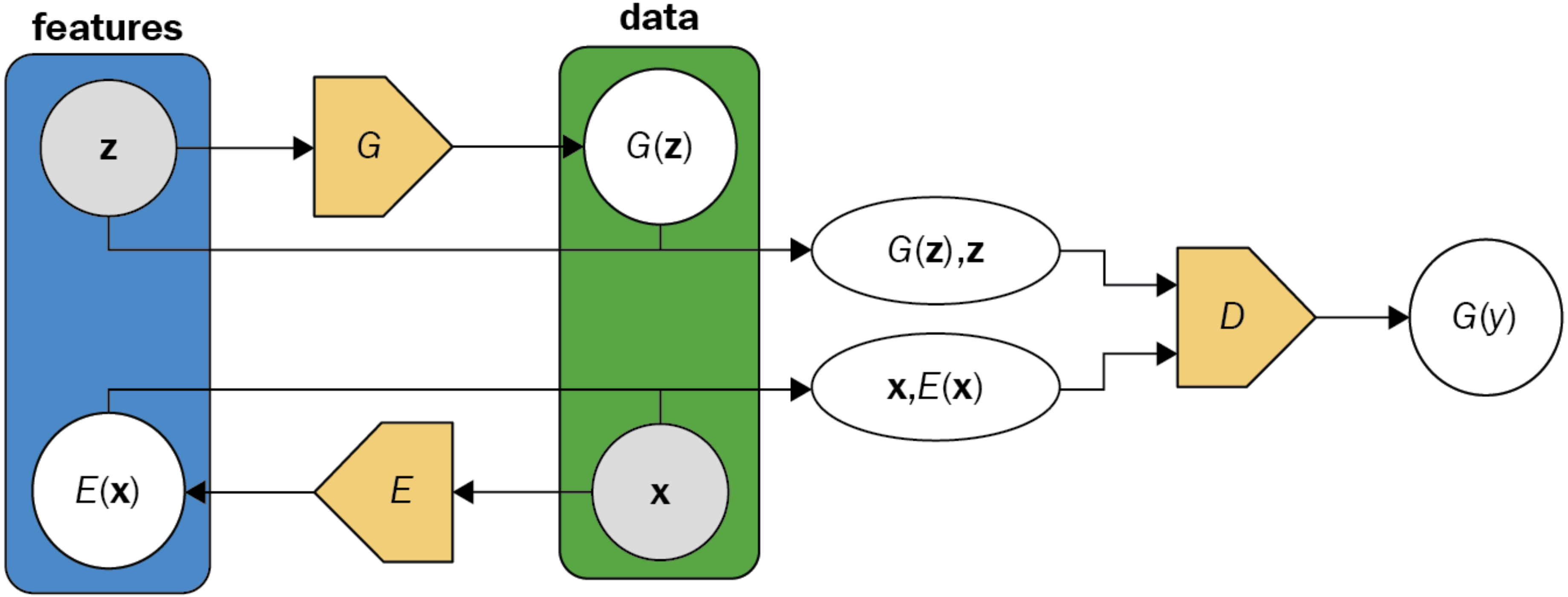
MNIST

Faces



CIFAR 10

Bidirectional GAN (BiGAN)



Conditional GAN (cGAN)

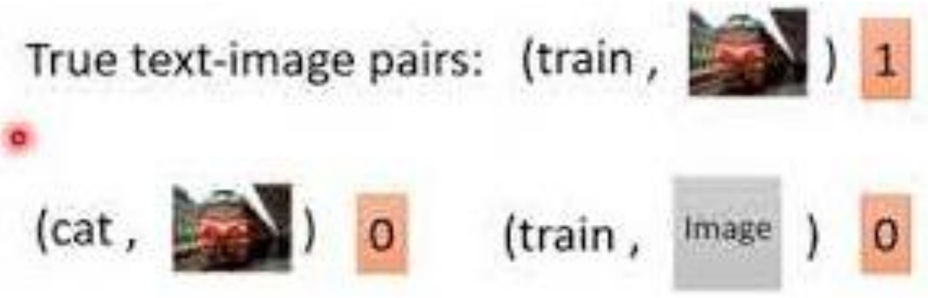
Generator

Discriminator

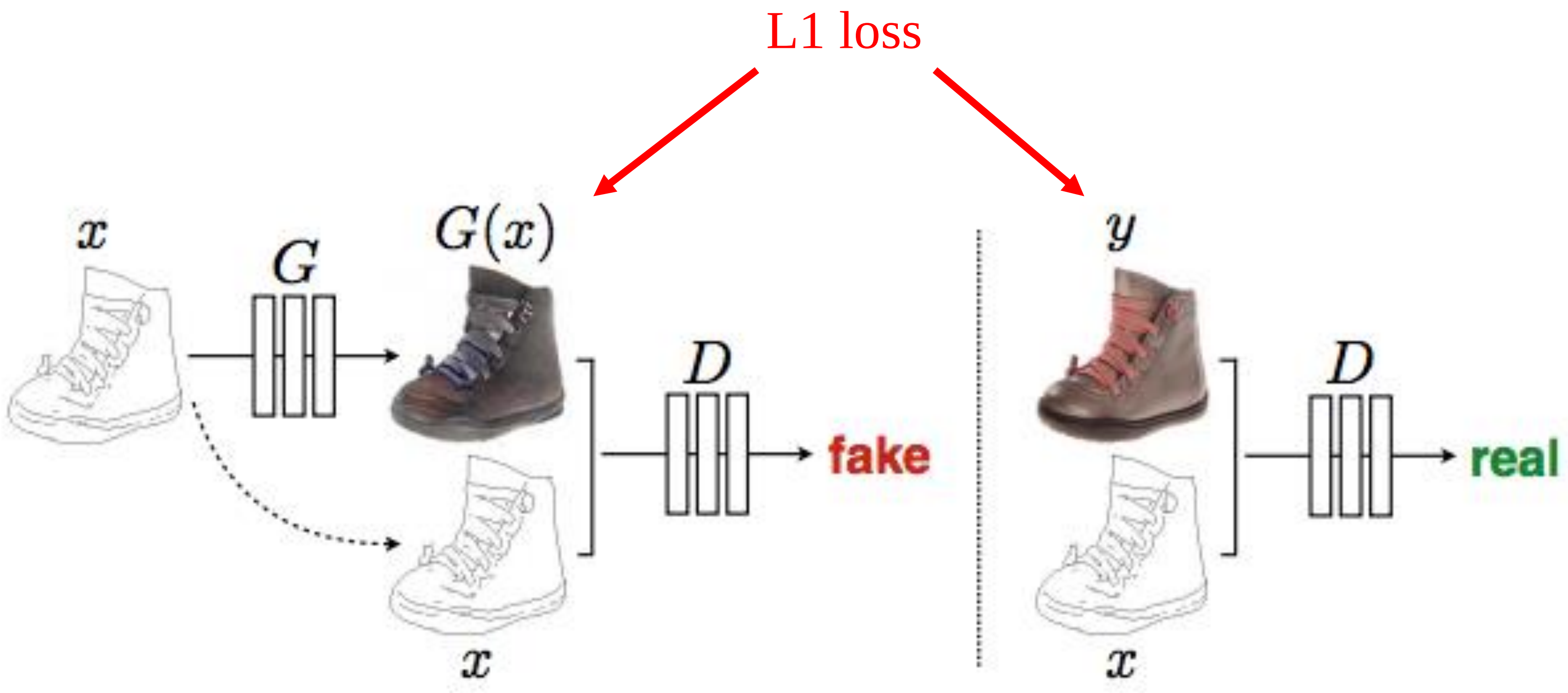
Conditional GAN (cGAN)

Generator

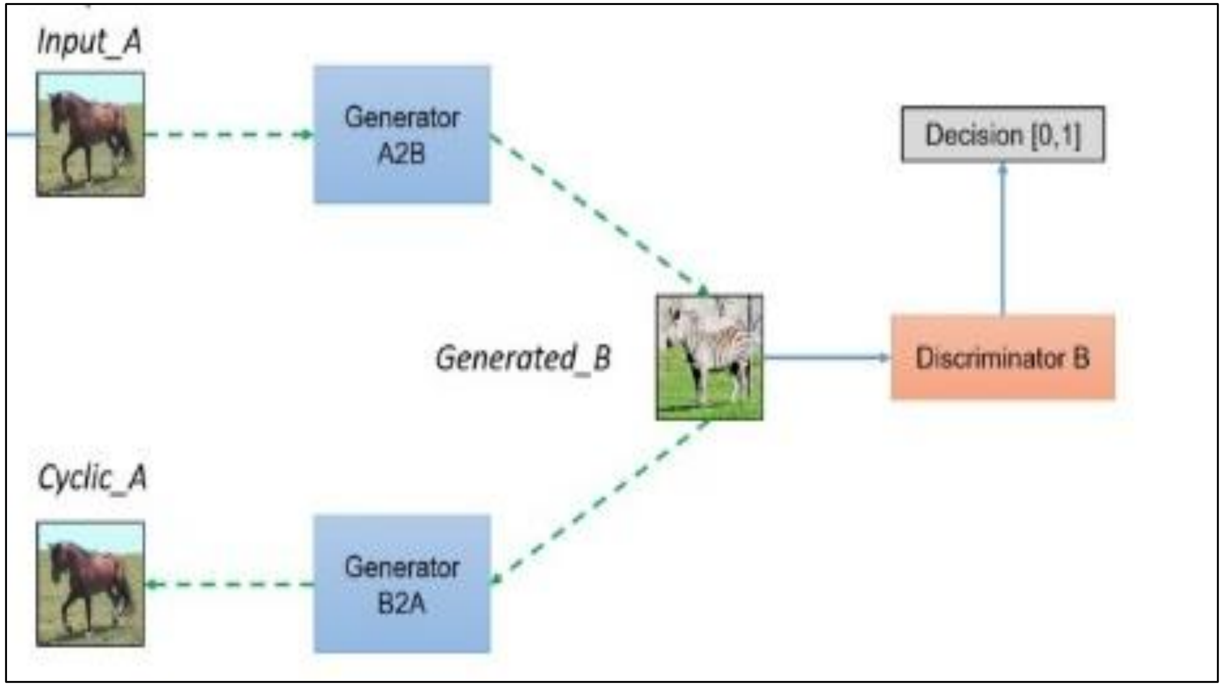
Discriminator



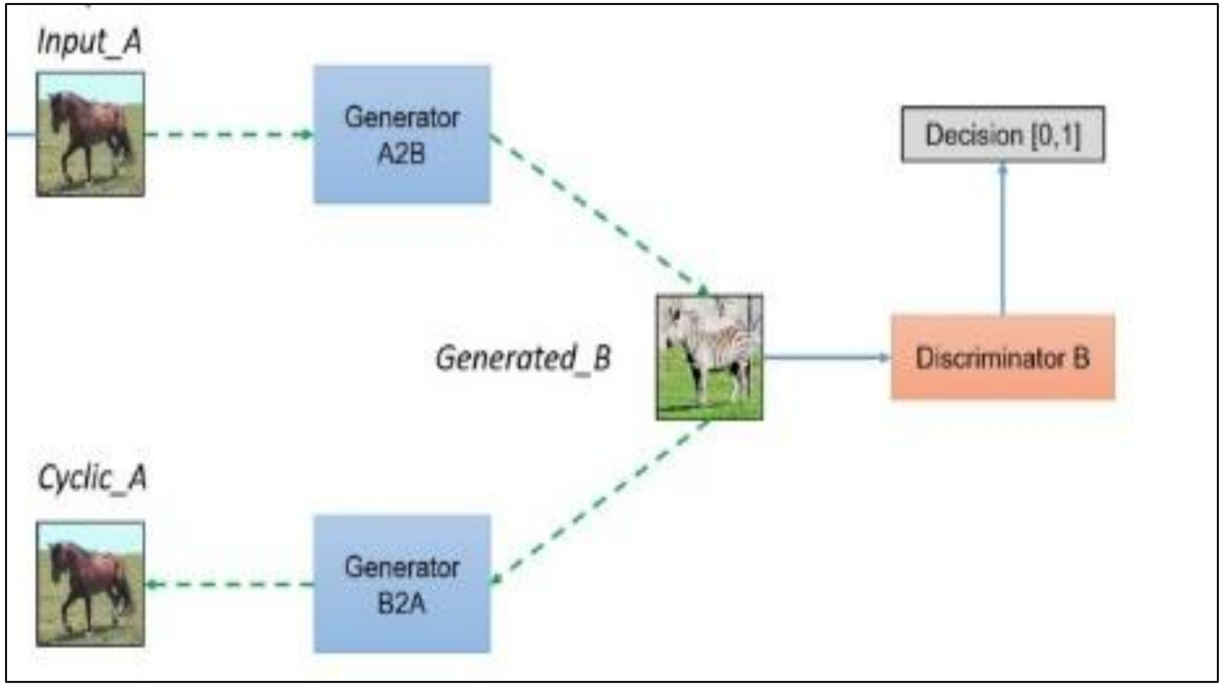
Pix2Pix: Type of cGAN

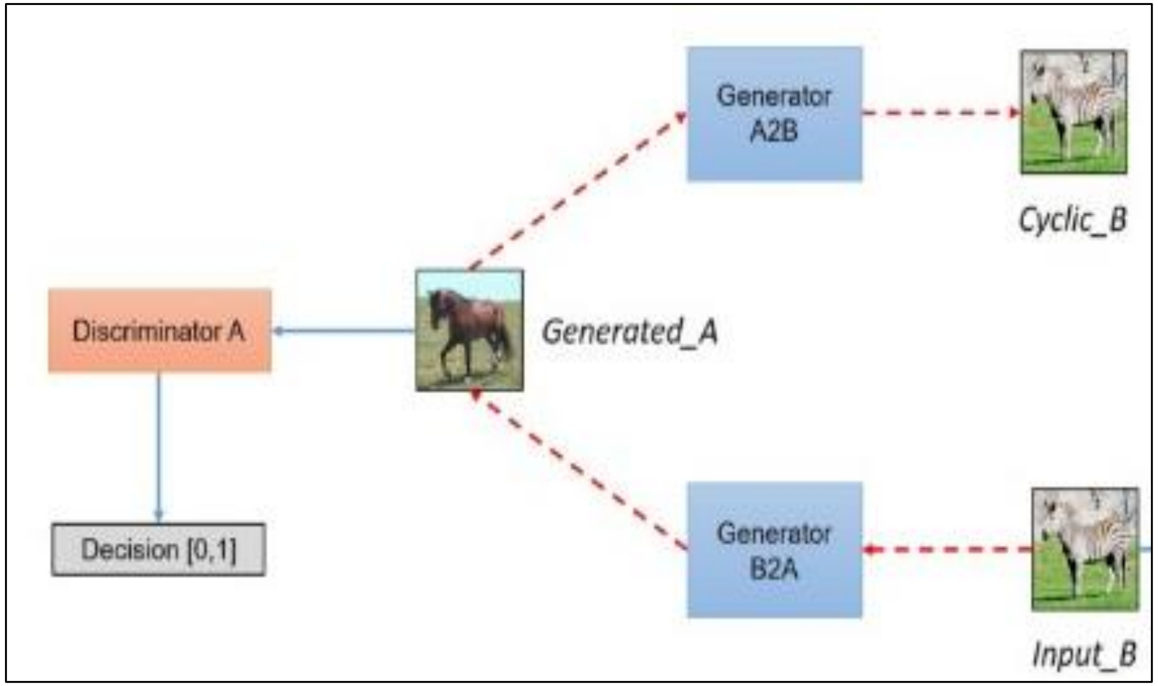


CycleGAN: Unsupervised Pix2Pix



CycleGAN: Unsupervised Pix2Pix





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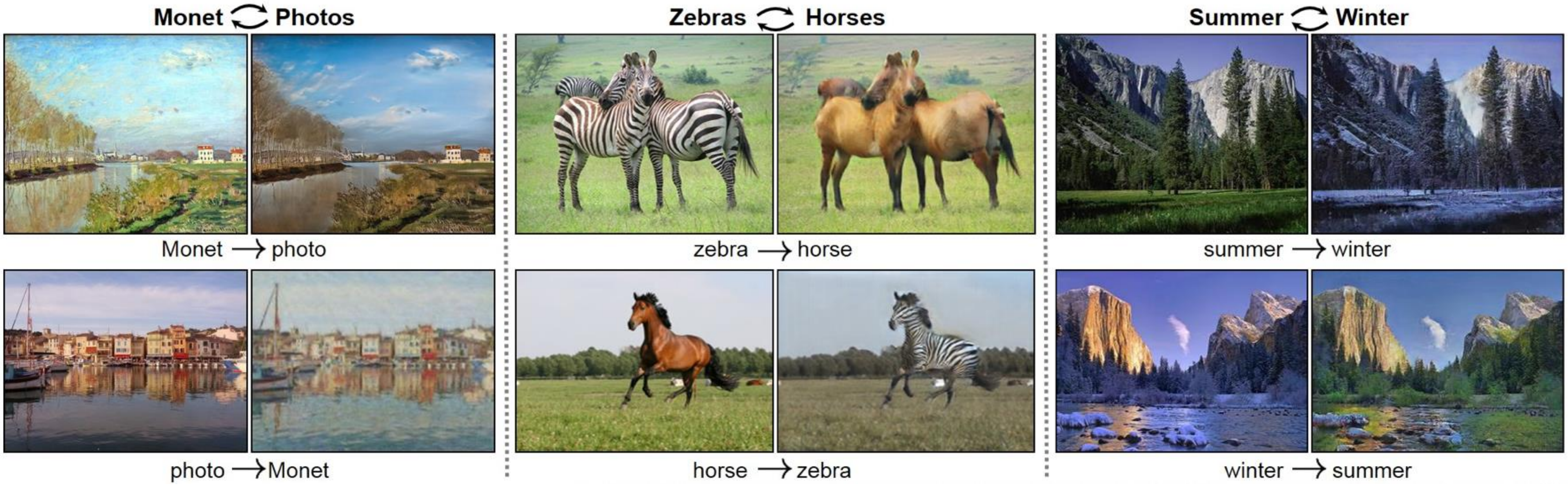
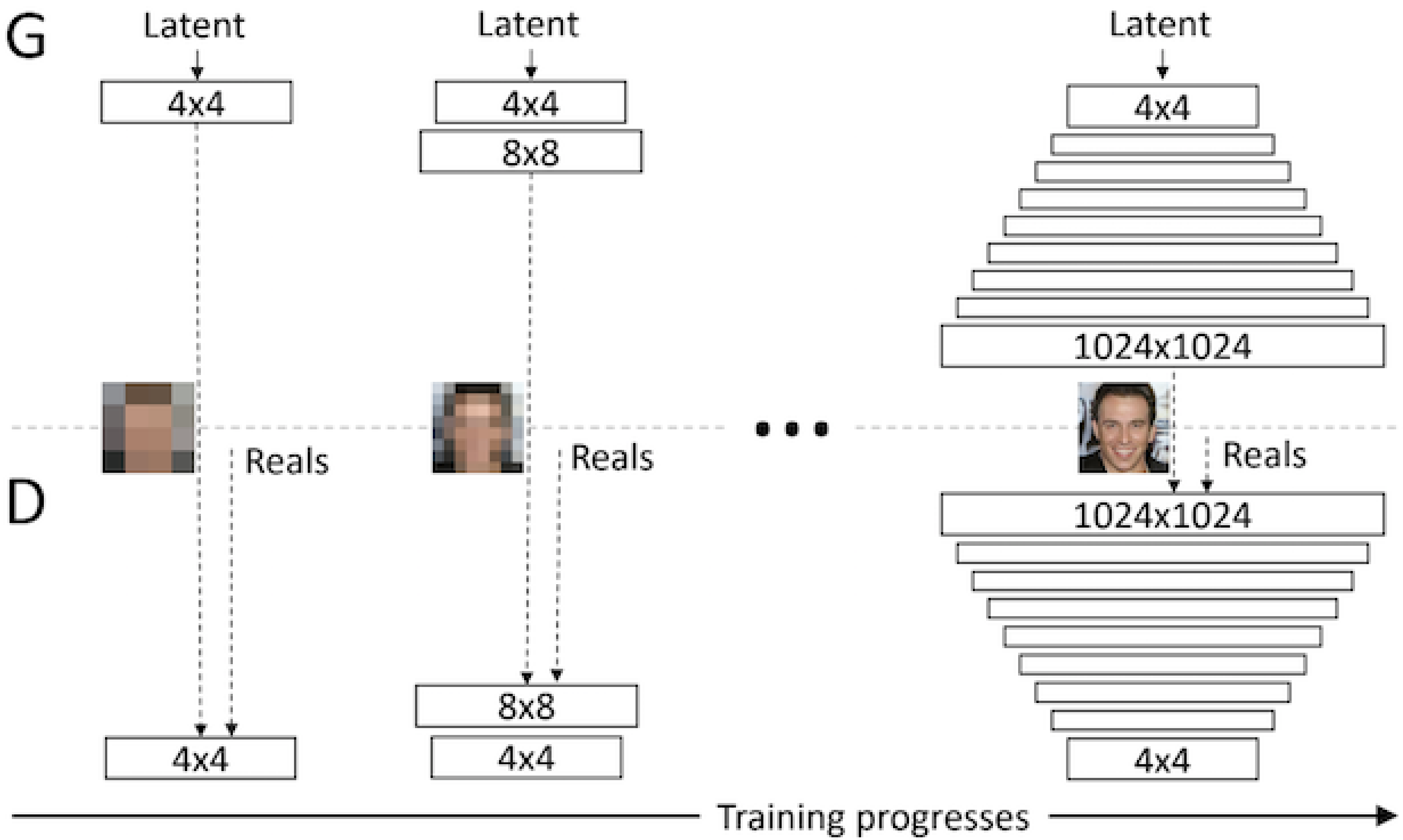
CycleGAN Results



Progressive Growing of GANs



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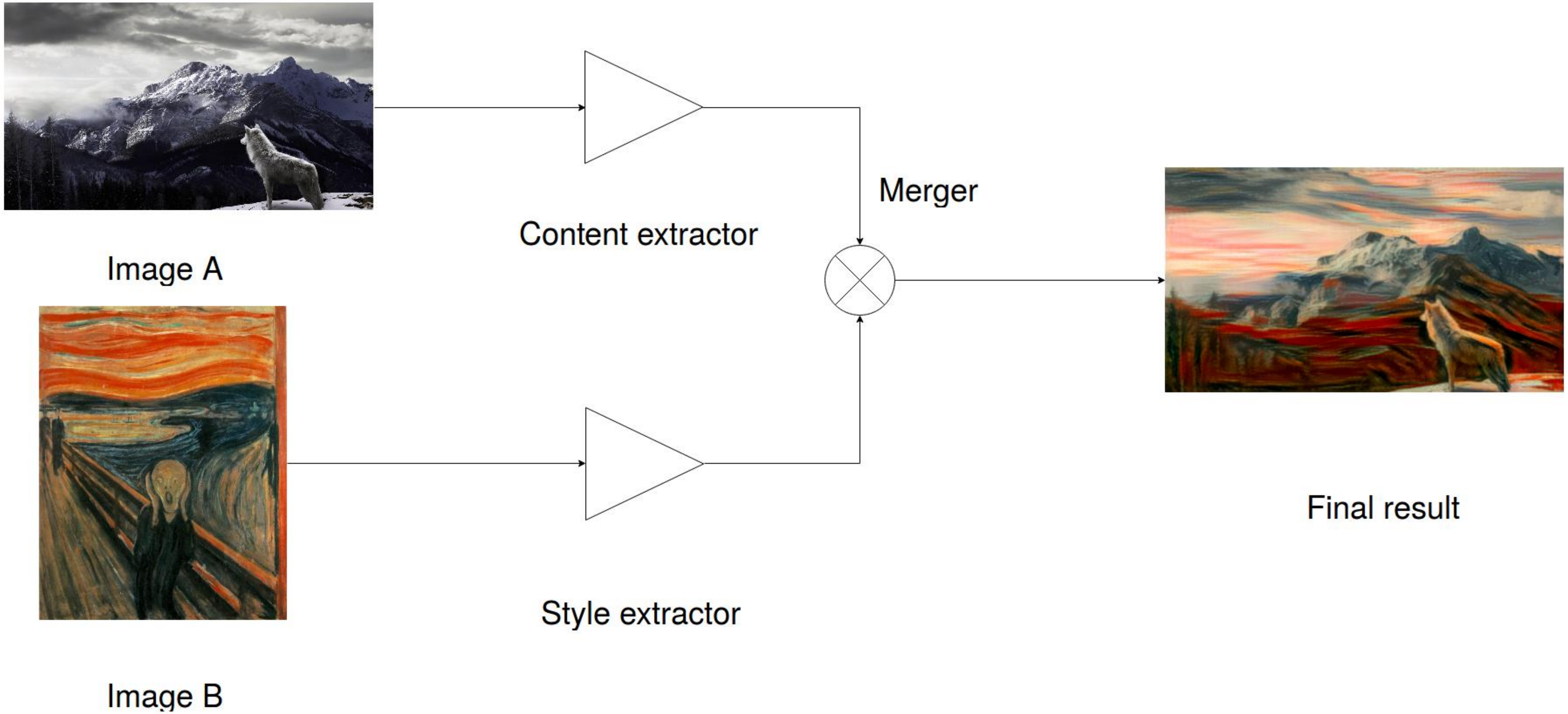
Progressive GAN Results

Celebrities

Bedrooms

Objects

Application: Neural Style transfer



Application: 3D GAN