Generative Adversarial Network

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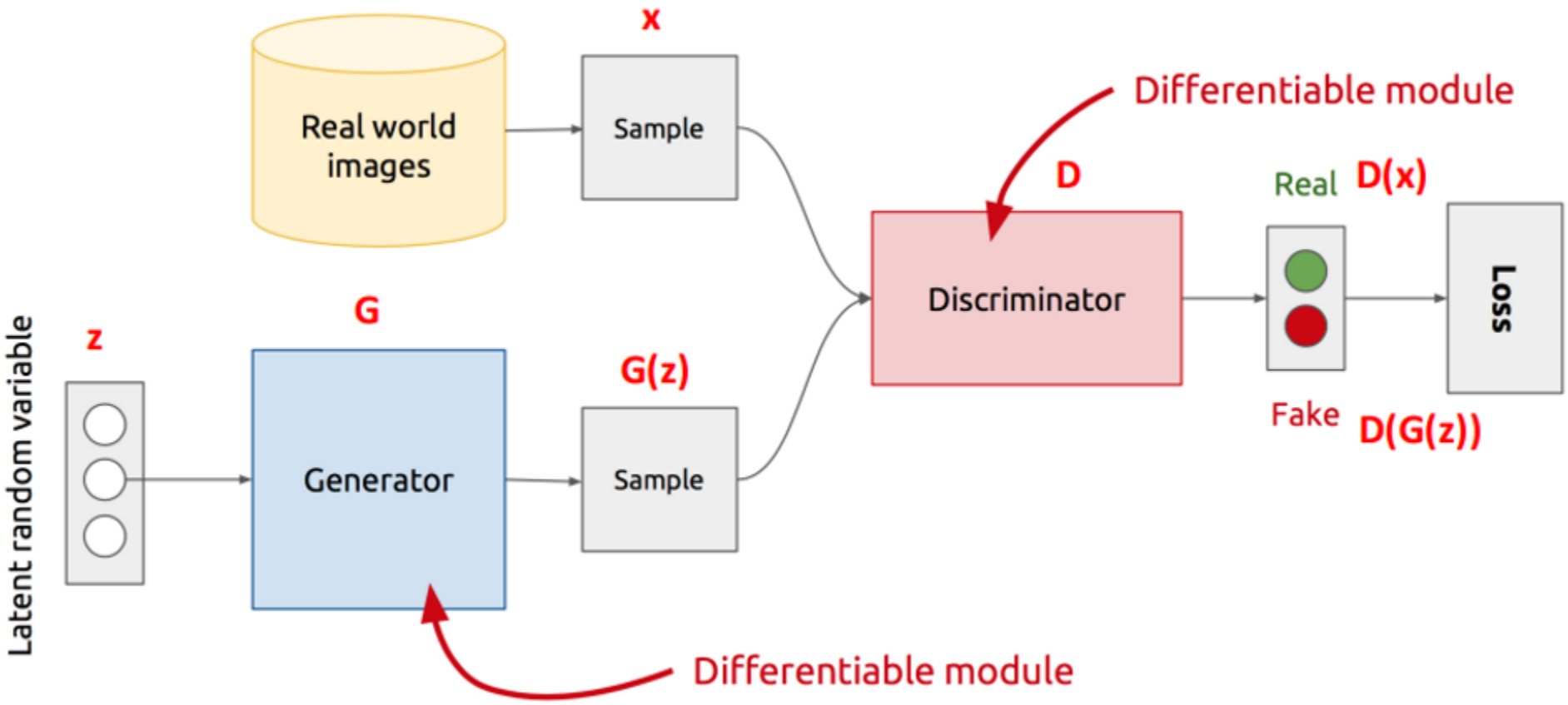
Why GAN

- All we see so far are discriminative models
  - Given an input, predict output

- Limitation
  - Can’t model the probability of input
  - Thus not able to sample from input (generate new input)

GAN Vanilla Architecture



Algorithm 1 Minibatch stochastic gradient descent training of generative adversarial nets. The number of steps to apply to the discriminator, k, is a hyperparameter. We used $k = 1$, the least expensive option, in our experiments.

for number of training iterations **do**

for k steps **do**

- Sample minibatch of m noise samples $\{\boldsymbol{z}^{(1)}, \ldots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
- Sample minibatch of m examples $\{\boldsymbol{x}^{(1)}, \ldots, \boldsymbol{x}^{(m)}\}$ from data generating distribution $p_{\text{data}}(\boldsymbol{x})$.
- Update the discriminator by ascending its stochastic gradient:

$$\nabla_{\theta_d} \frac{1}{m} \sum_{i=1}^{m} \left[\log D\left(\boldsymbol{x}^{(i)}\right) + \log\left(1 - D\left(G\left(\boldsymbol{z}^{(i)}\right)\right)\right) \right].$$

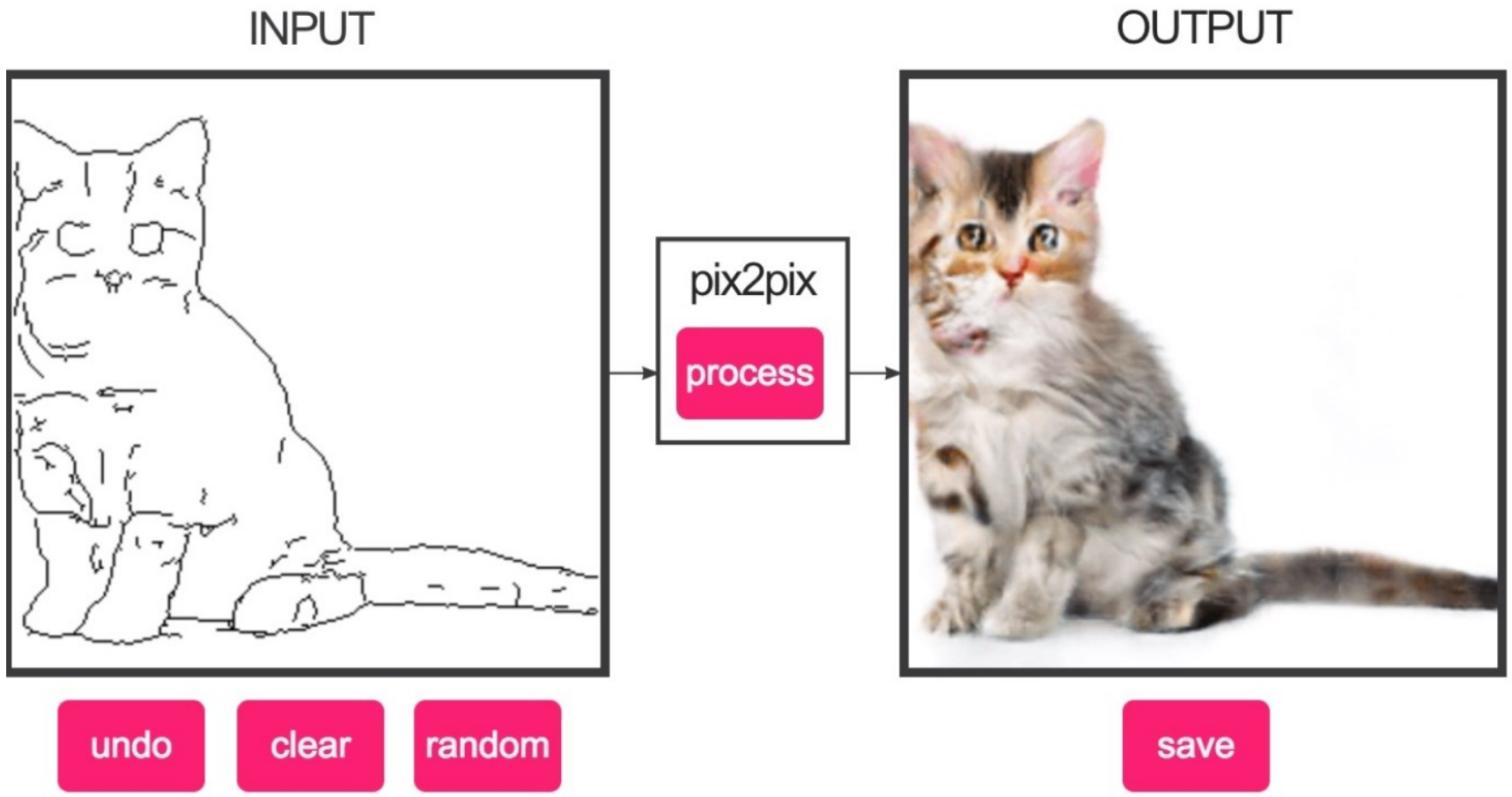
end for

- Sample minibatch of m noise samples $\{\boldsymbol{z}^{(1)}, \ldots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
- Update the generator by descending its stochastic gradient:

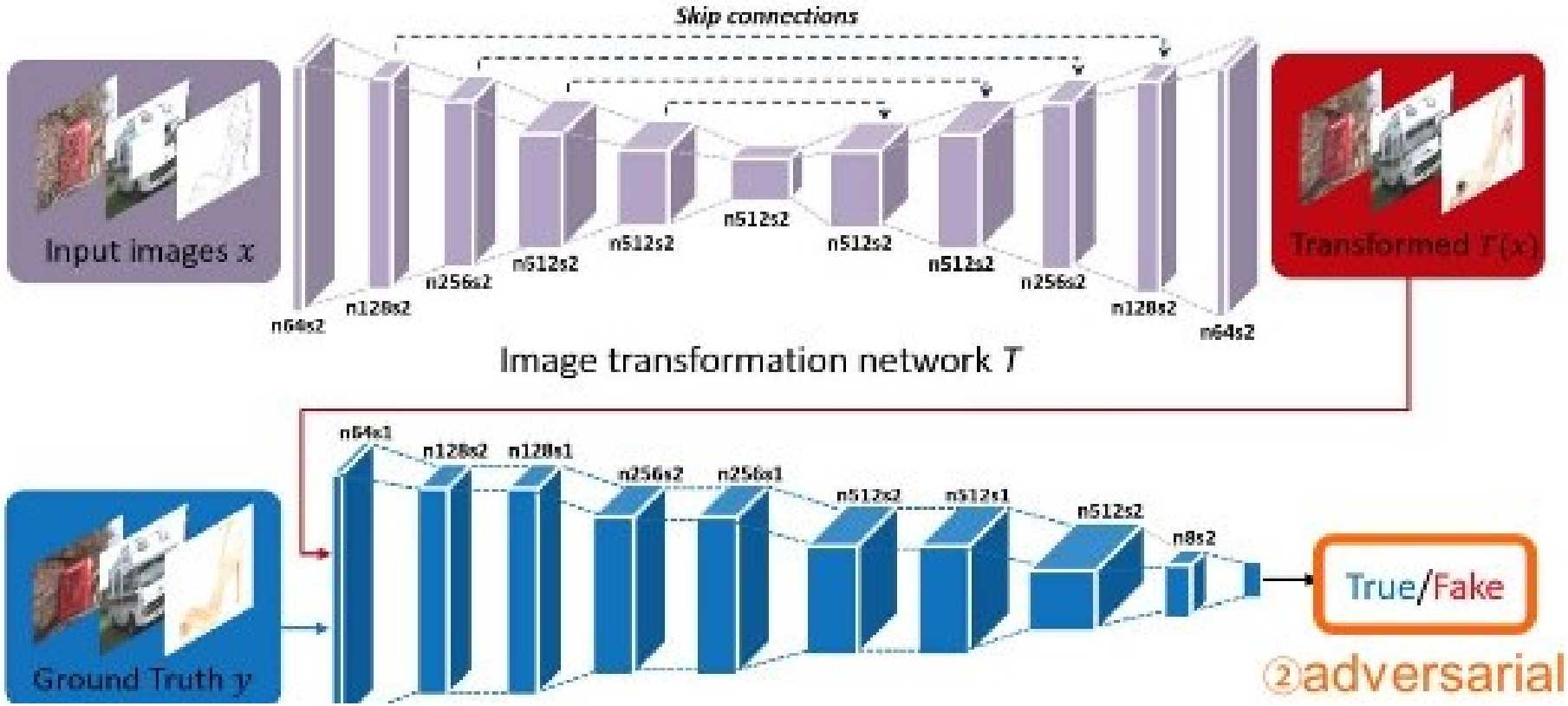
$$\nabla_{\theta_g} \frac{1}{m} \sum_{i=1}^{m} \log\left(1 - D\left(G\left(\boldsymbol{z}^{(i)}\right)\right)\right).$$

end for

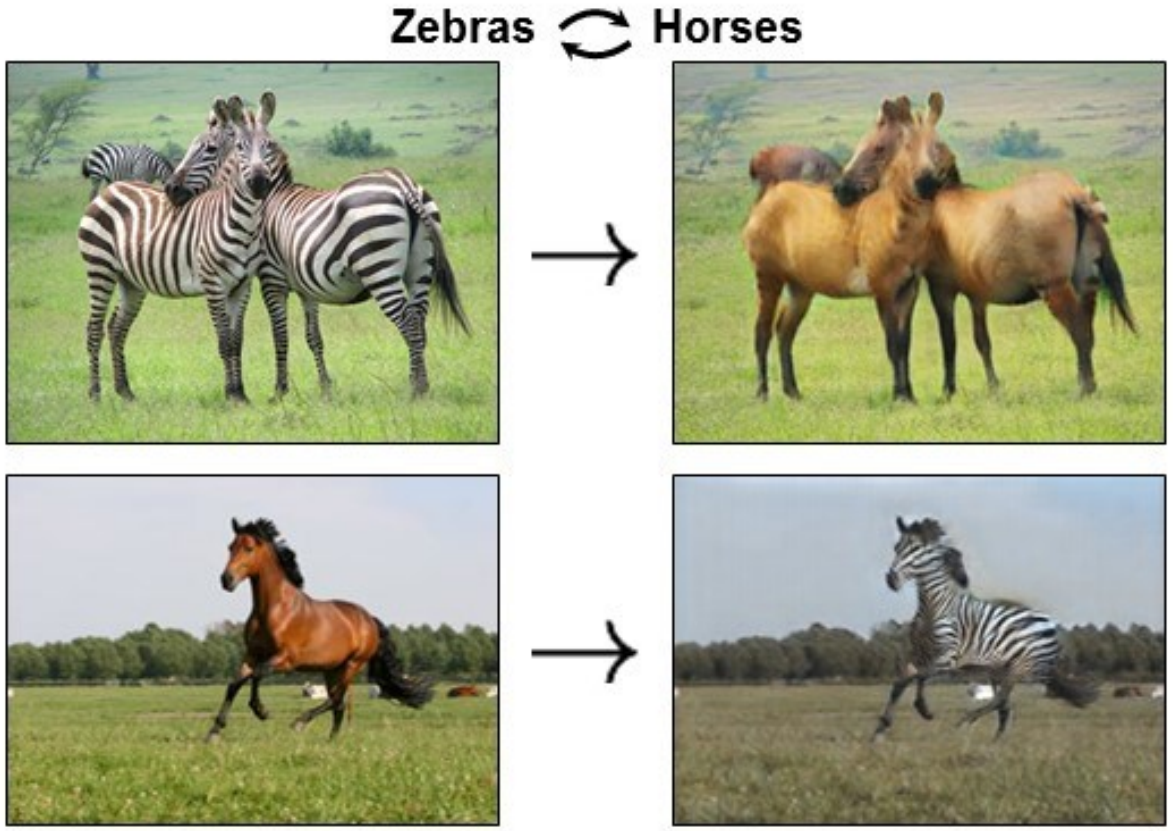
Pix2Pix

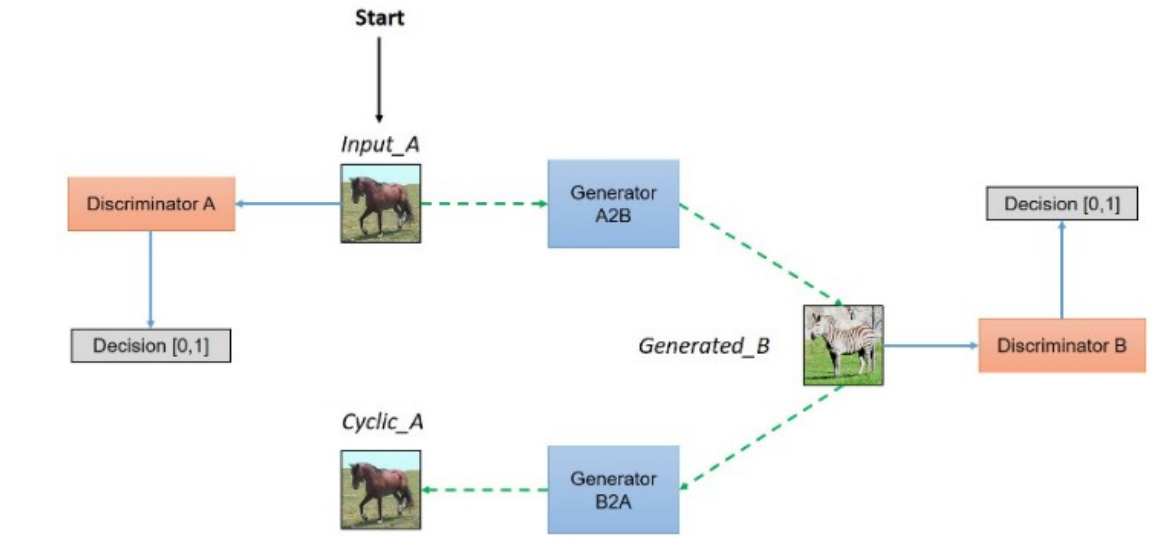


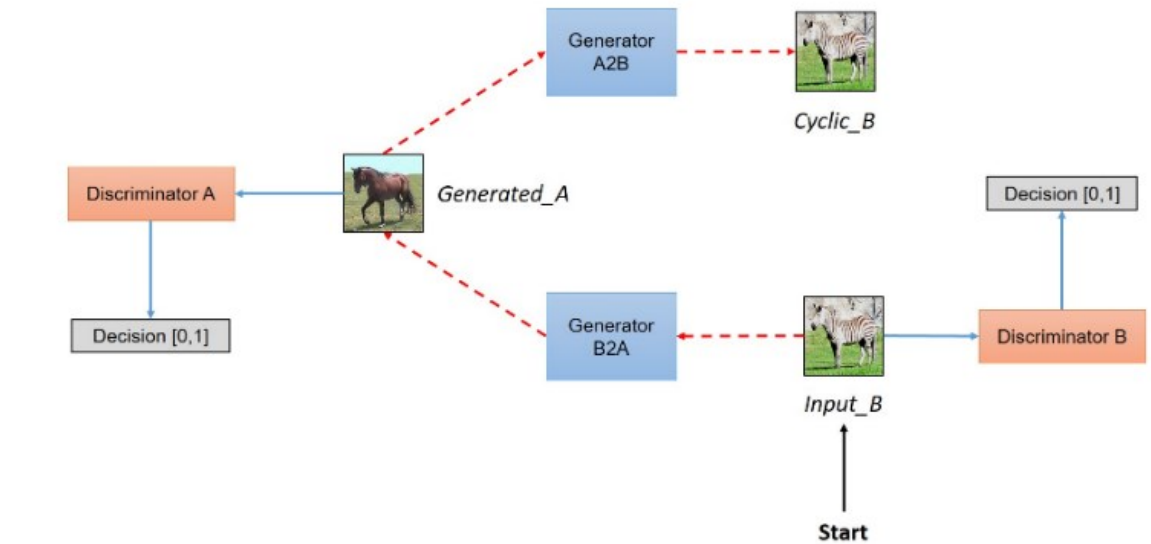
Pix2Pix (①+②)


Skip connections
Input images x
n64s2
n128s2
n256s2
n512s2
n512s2
n512s2
n512s2
n512s2
n256s2
n128s2
n64s2
Transformed $T(x)$
Image transformation network T
Ground Truth y
n64s1
n128s2
n128s1
n256s2
n256s1
n512s2
n512s1
n512s2
n8s2
True/Fake
②adversarial

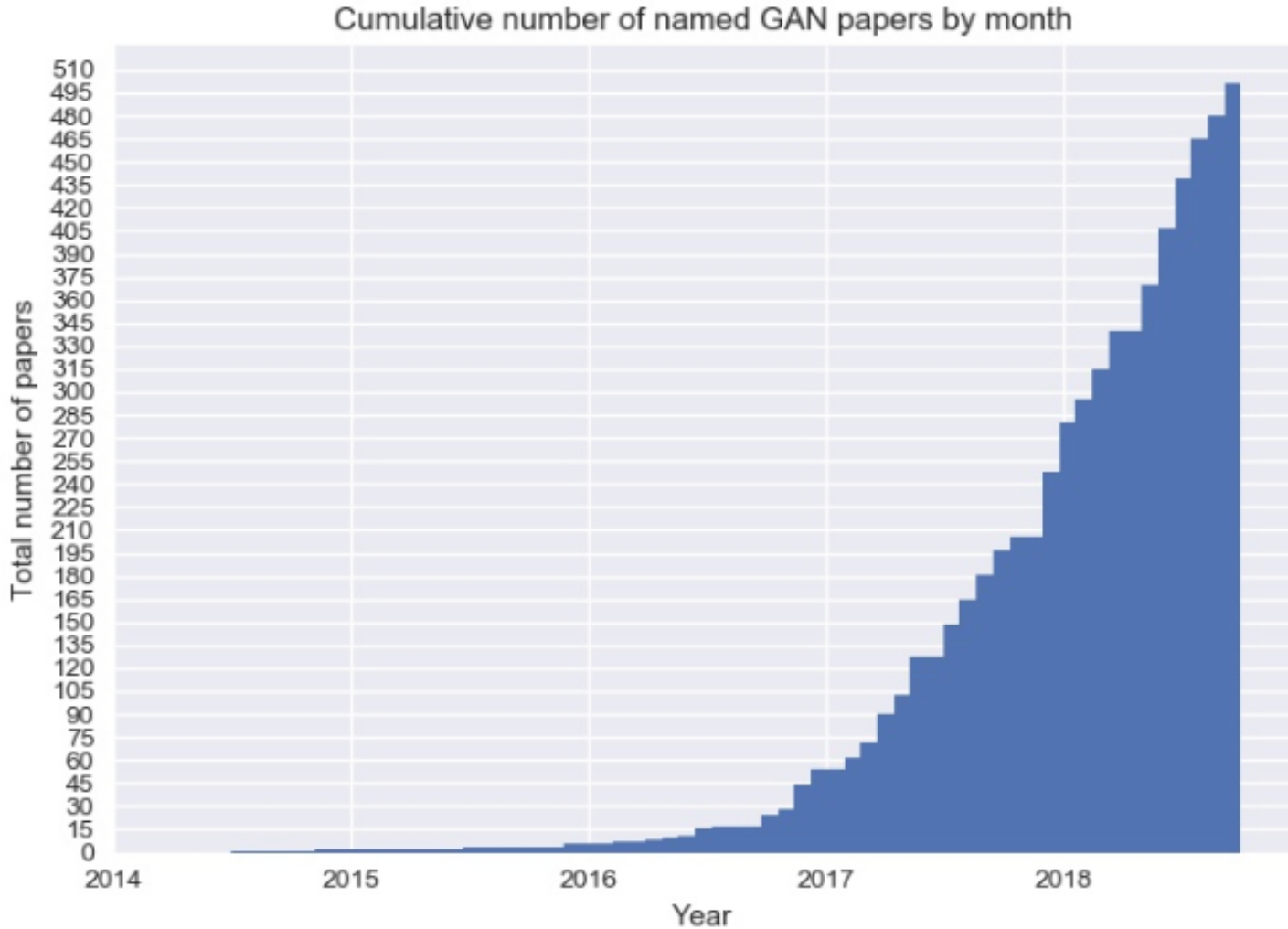
CycleGAN







Simplified view of CycleGAN architecture



https://github.com/hindupuravinash/the-gan-zoo

3.5 Years of Progress on Faces

2014 2015 2016 2017

(Brundage et al. 2018)

<2 Years of Progress on ImageNet

Odena et al 2016

Miyato et al 2017

Zhang et al 2018

(Goodfellow 2018)

Andrew et al 2018

How to learn all these?