DL Dev Course: Week 08
GANs

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What is a
Generative Adversarial Network?

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“is the most interesting idea in the last 10 years in ML, in my opinion”

Yann LeCun

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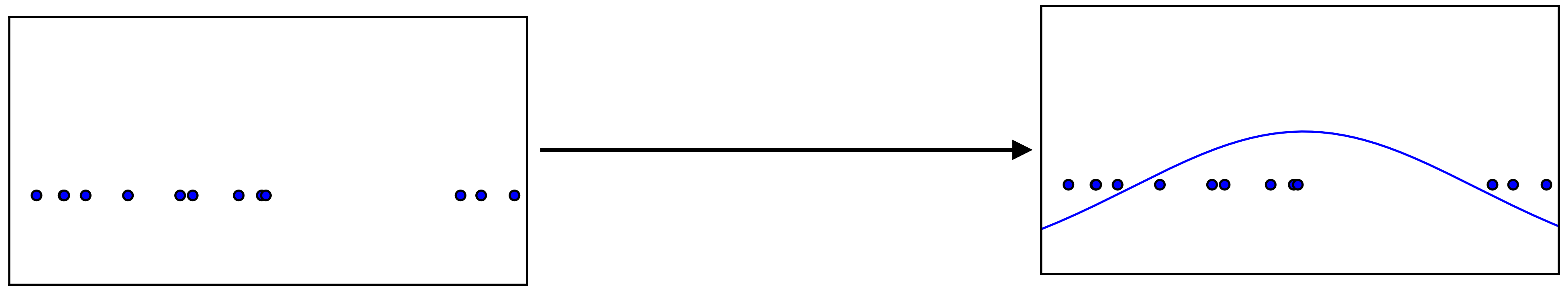
Generative Modeling

- Density estimation



(Goodfellow 2016)

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Generative Modeling

Training examples

Model samples

(Goodfellow 2016)

Supervised Learning

- Creating a function that maps x -> y.
- $f(x) = y$
- Conditional Probability $P(y|x)$
- Standard Classification models
- MNIST $f(x) = y$

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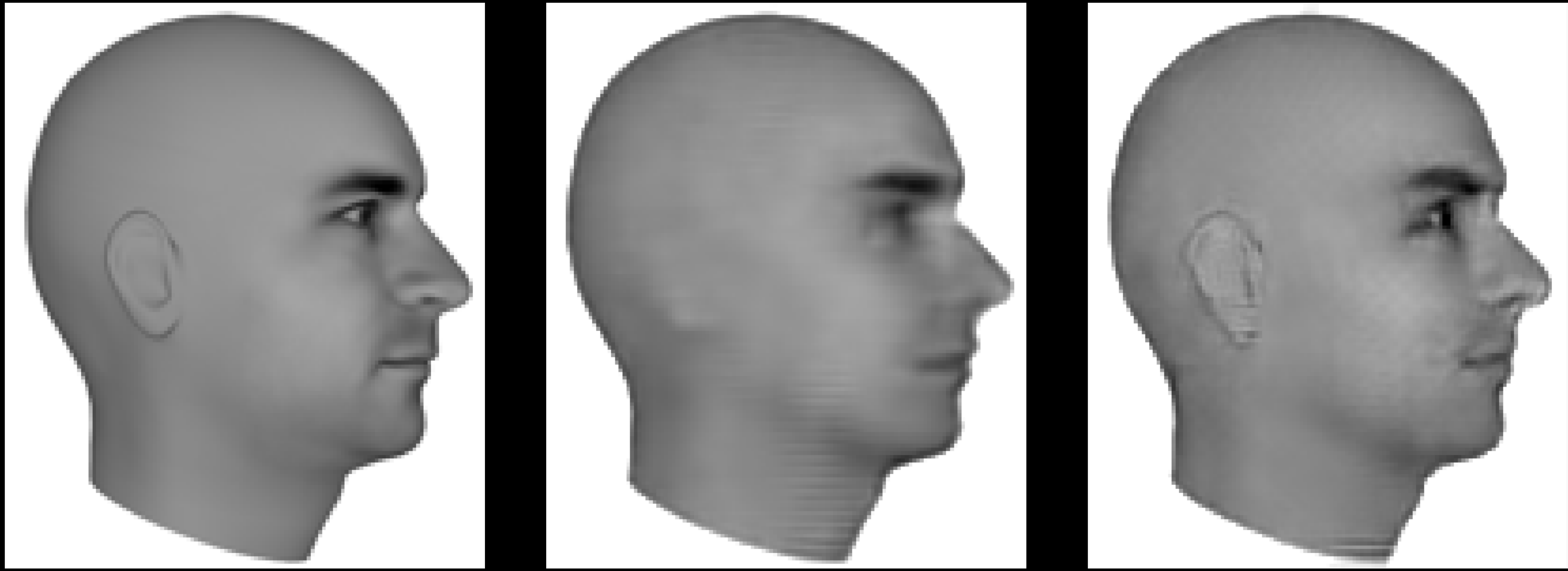
Pen Fall

Next Video Frame Prediction

Ground Truth | MSE | Adversarial



(Lotter et al 2016)

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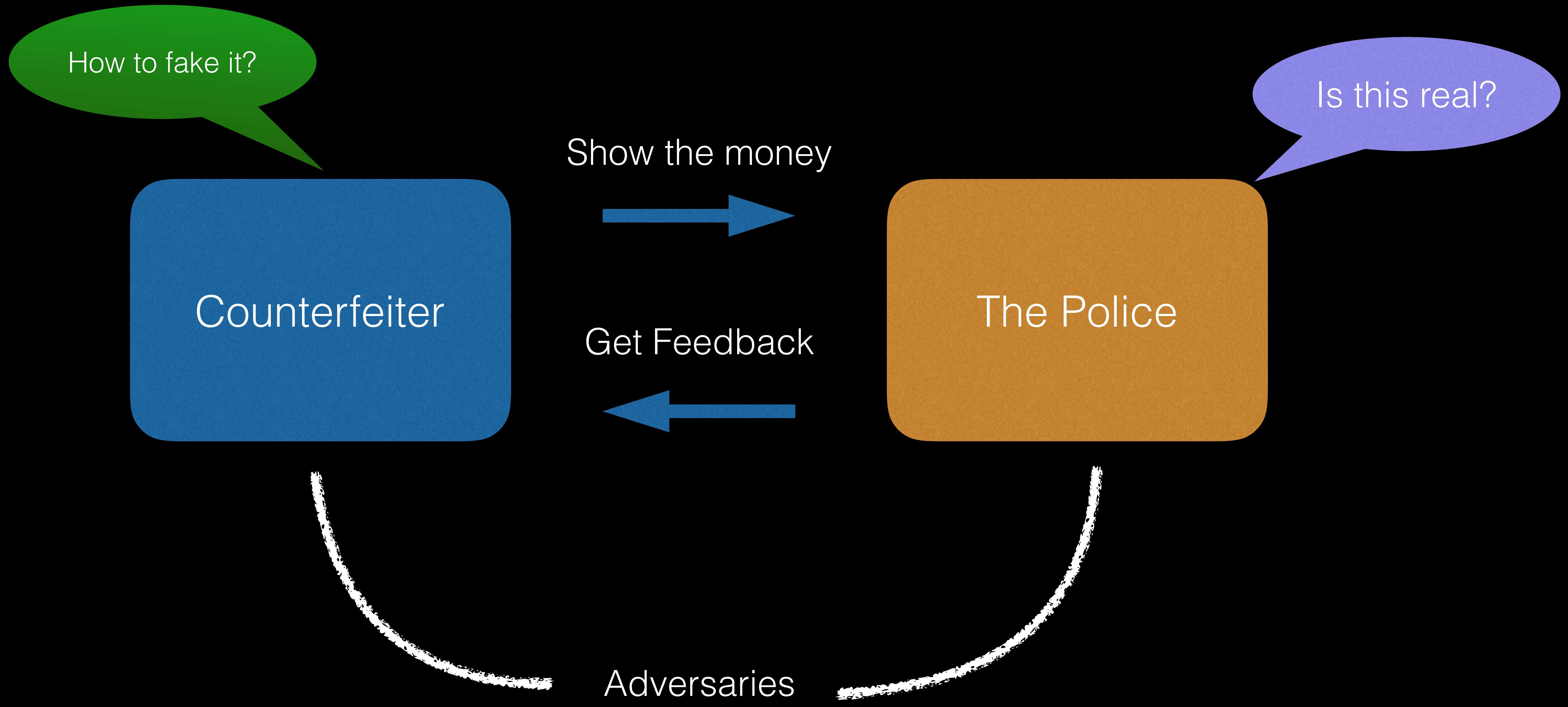
(Goodfellow 2016)

GANs

- Introduced in by Ian Goodfellow in 2014
- Took off a lot in 2016
- Now lots of type and variations
- DCGAN, Wasserstein GAN, StackGAN, Disco GAN, Progressively Growing GAN etc

The Analogy



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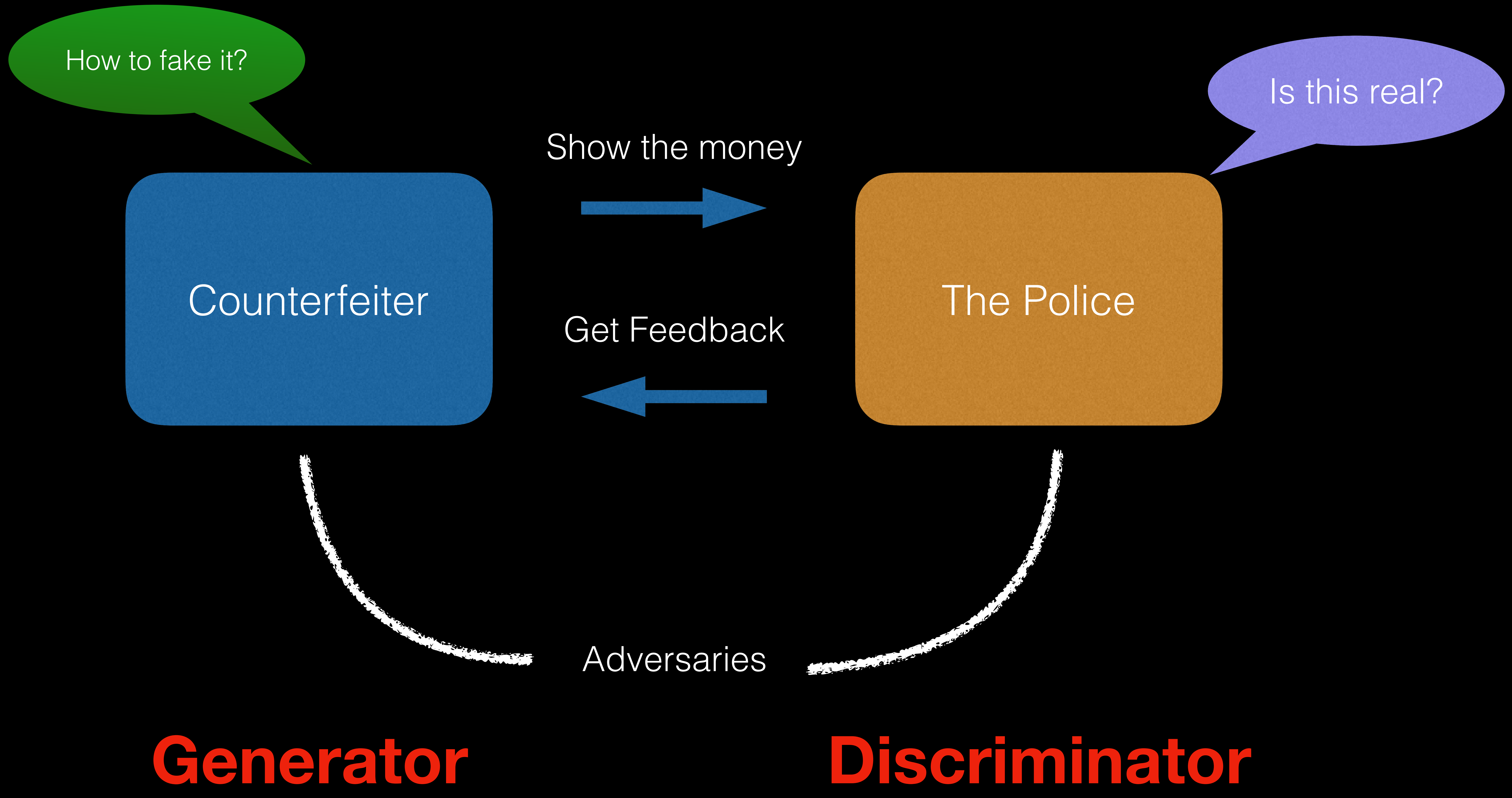
The Analogy



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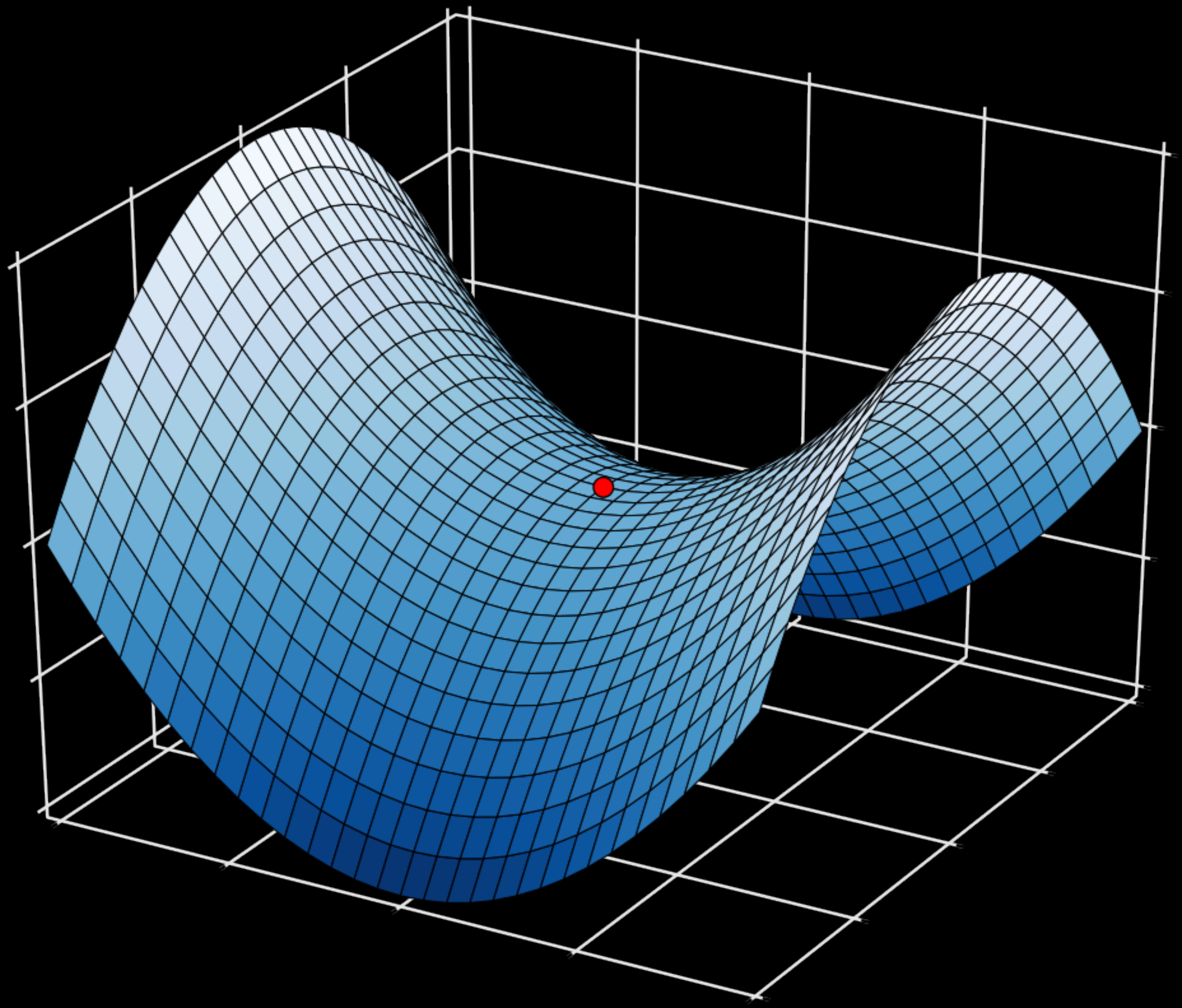
Adversarial Networks

- The 2 networks fight it out
- The Discriminator is trying to reduce loss of predicting real vs fake
- The Generator is trying to maximize it’s ability to create a fake sample that The Discriminator classifies as real
- It’s a Minimax game

The Fight of Optimization



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Adversarial Loss

- D Loss = D Loss on training images + D Loss on created images
- G Loss = D Loss on created images
- Total Loss = D Loss + G Loss

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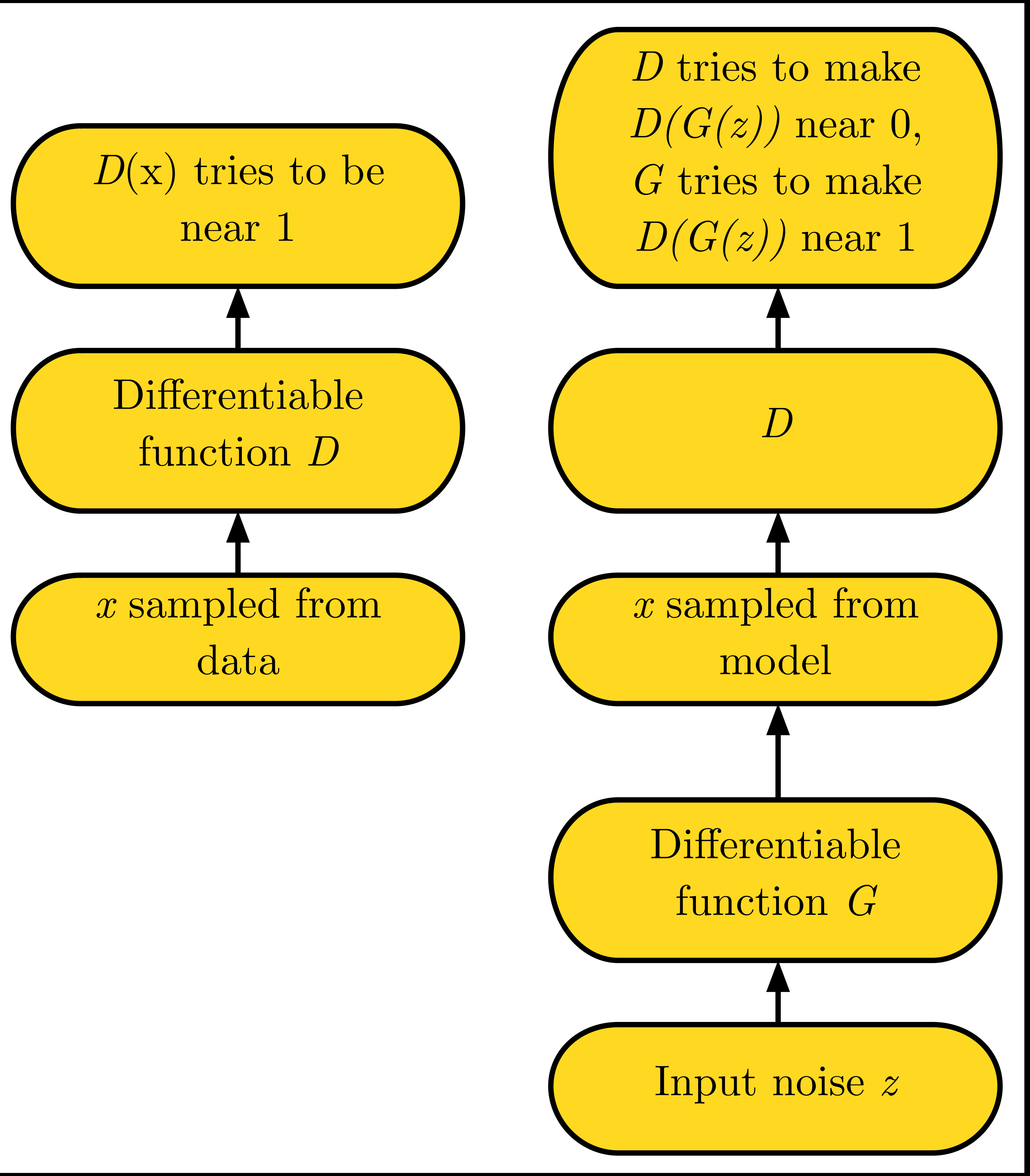
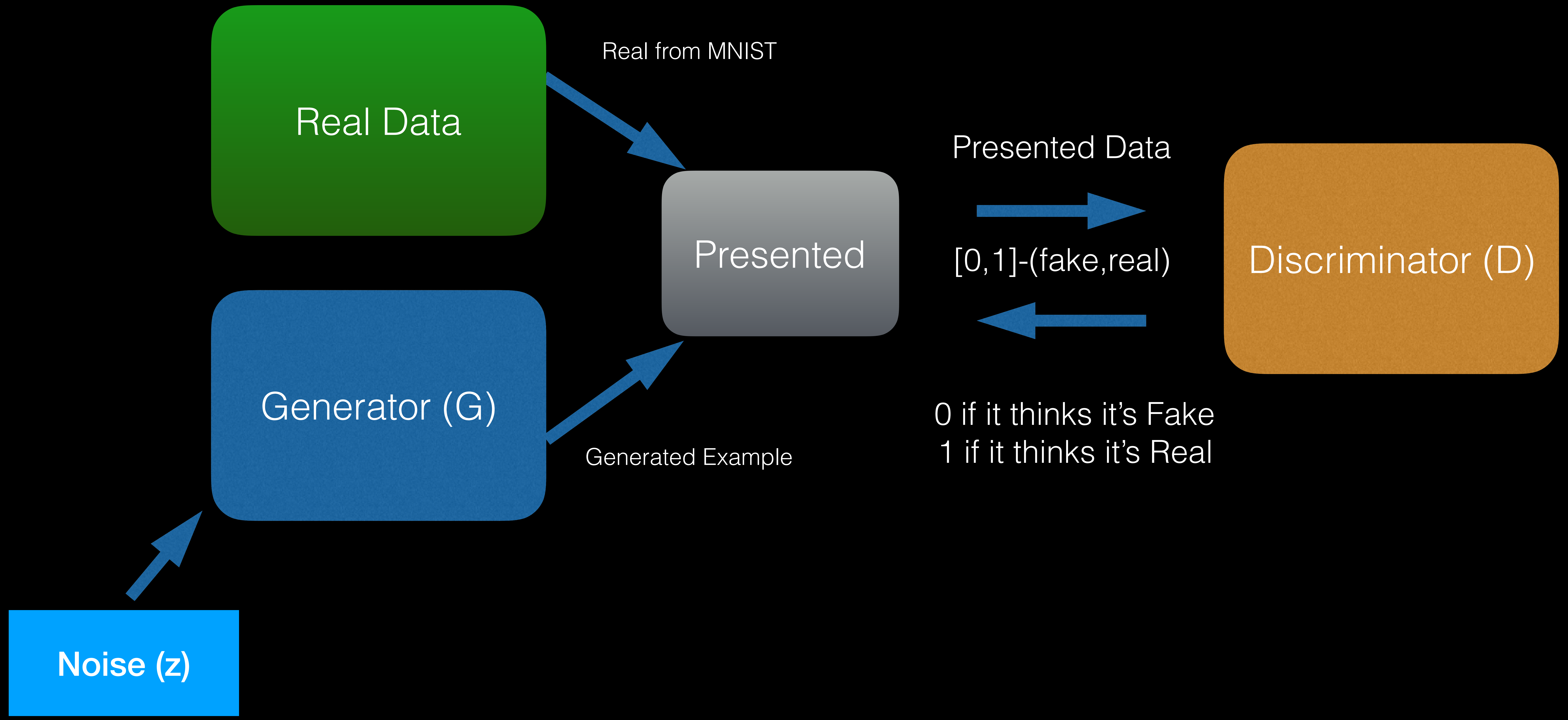
The Framework

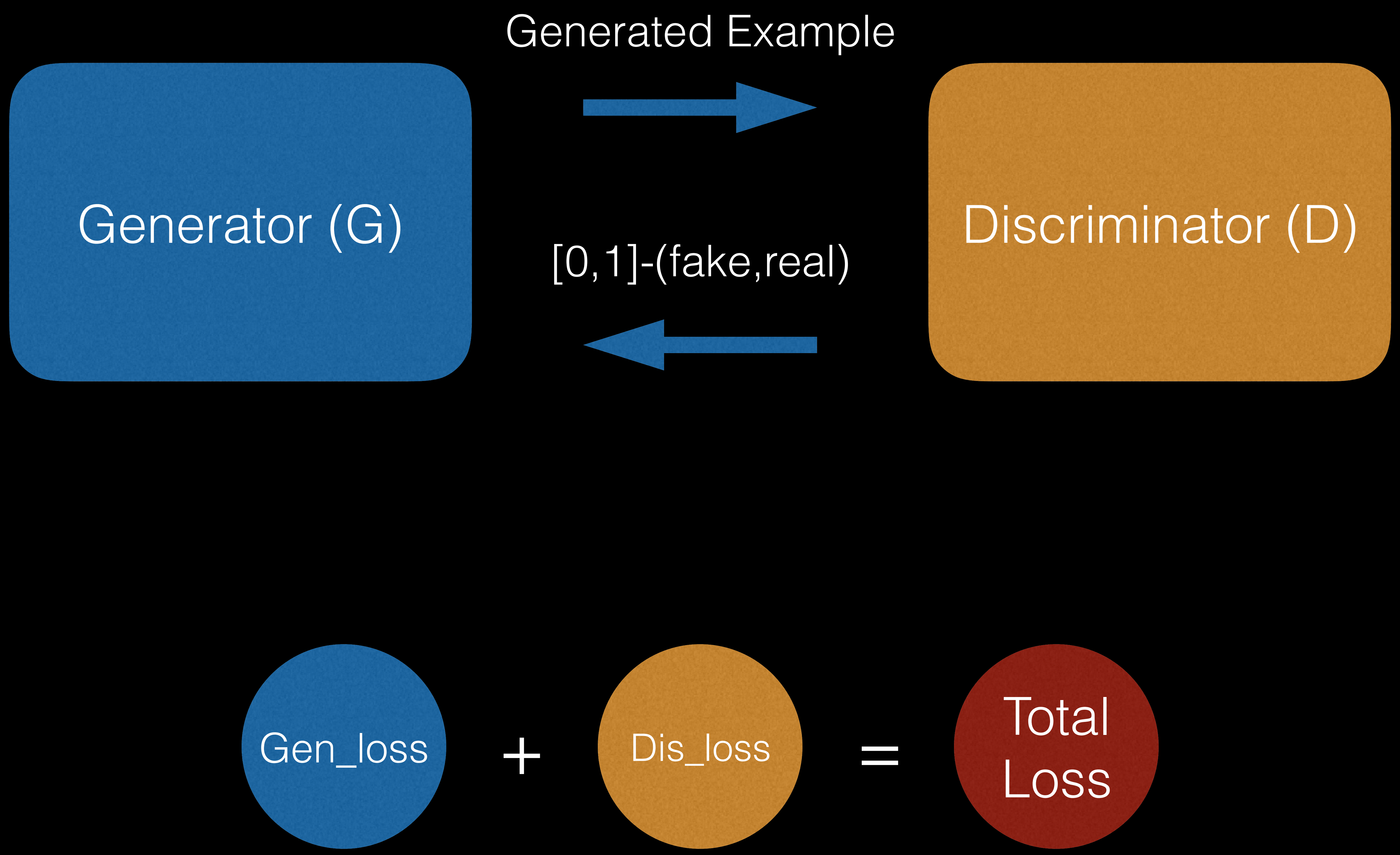


(Goodfellow 2016)

The Vanilla GAN



The Network


Generated Example
Generator (G)
Discriminator (D)
[0,1]-(fake,real)
Gen_loss
+
Dis_loss
=
Total Loss

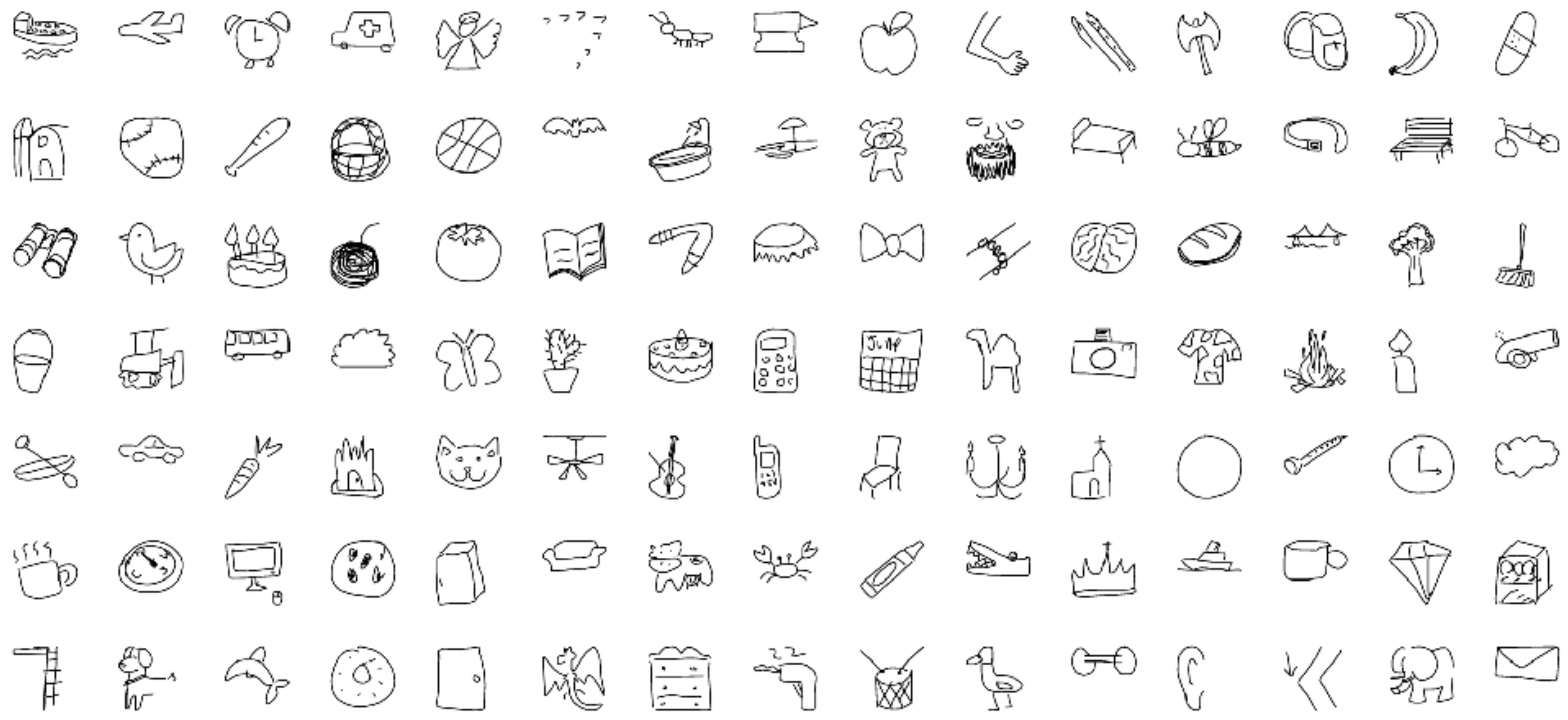
Quickdraw Dataset

What do 50 million drawings look like?

Over 15 million players have contributed millions of drawings playing Quick, Draw! These doodles are a unique data set that can help developers train new neural networks, help researchers see patterns in how people around the world draw, and help artists create things we haven't begun to think of. That's why we're open-sourcing them, for anyone to play with.

Select a drawing

↓



Code Time

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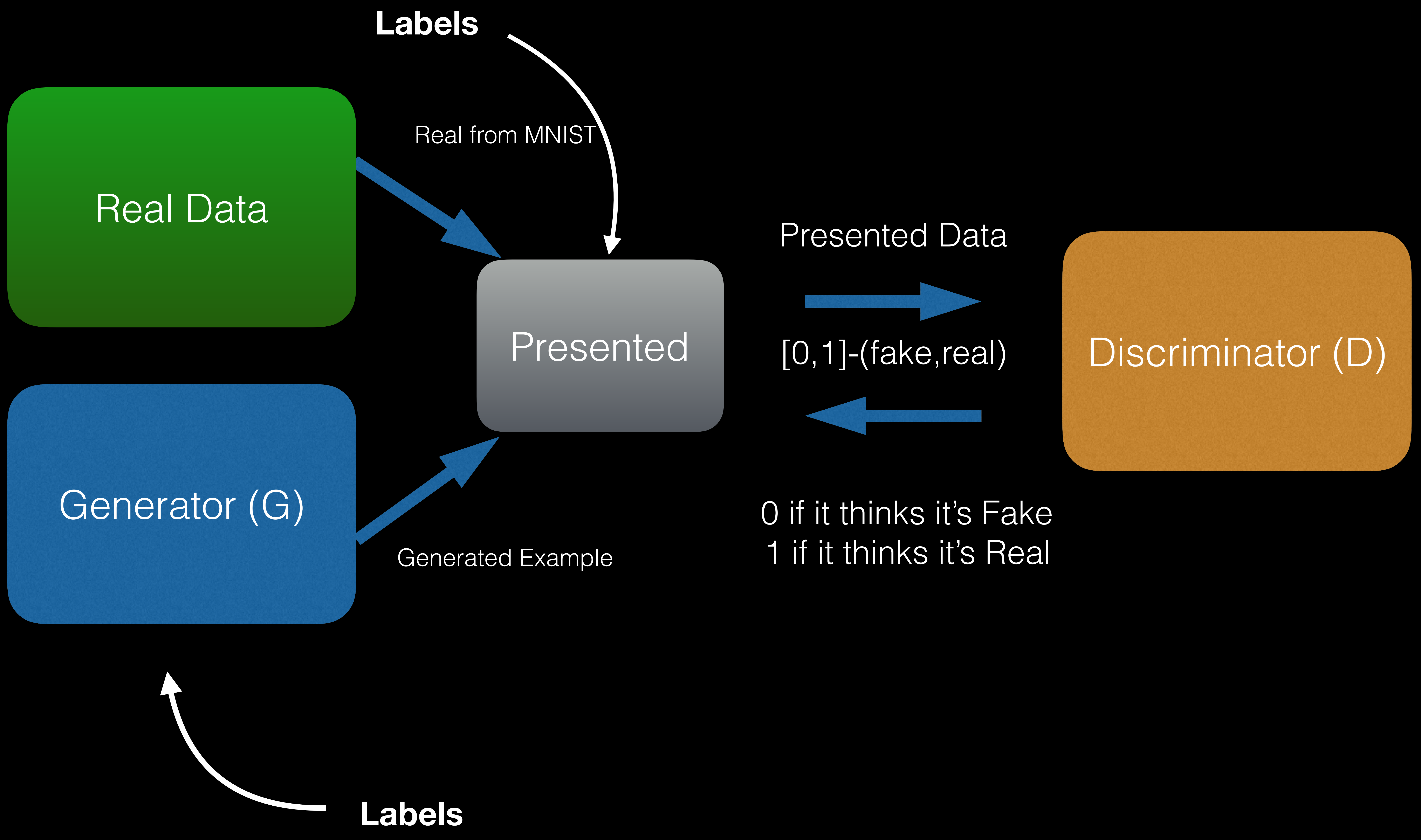
The Conditional GAN



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GANs Avantages

- They can learn to generate realistic samples
- They sample from the original data distribution so they can create examples that are plausible in that distribution
- They allow for many types of correct answers
- They can create never before seen but realistic looking pictures

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Disadvantages

- Still a long way to go
- So far haven't been very useful for real world applications.
- Not something that has yet been easy to do with text.
- While the appear to create the best examples, there is no clear way to measure them.

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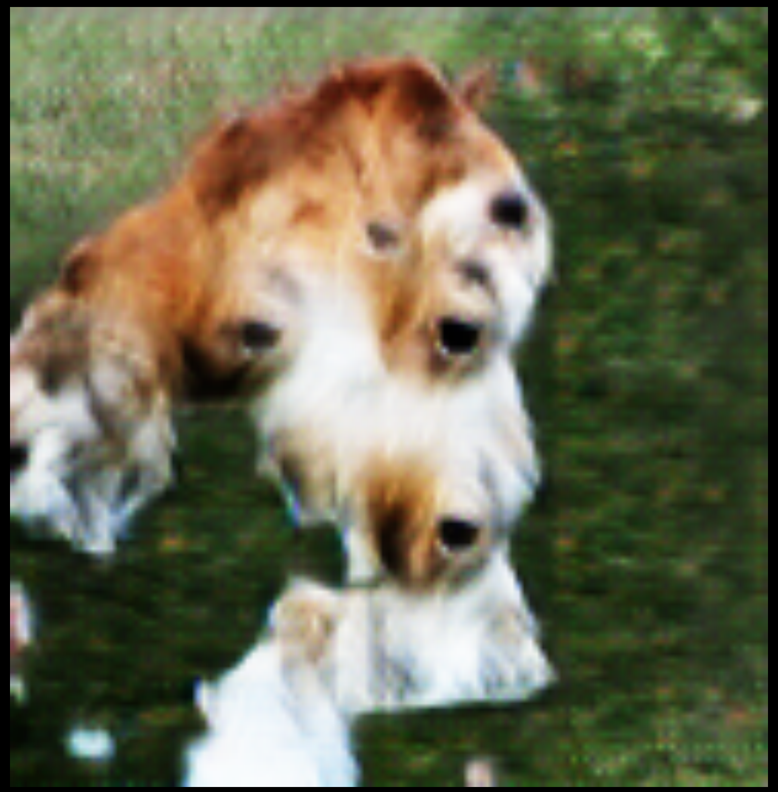
Problems with Counting



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(Goodfellow 2016)

Problems with Perspective







(Goodfellow 2016)

Problems of GANs

- Mode Collapse
- Can be much trickier to train than straight predictive networks
- They loose stability
- Hard to work with data like text due to words being discrete
- A lot of these problems are being solved as new papers come out eg. Wasserstein GAN

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Tips & Tricks

- Labels can help learning (CGAN)
- Clipping Weights (WGAN)
- Loss is not always the best indication
- Unequal training of Discriminator vs Generator
- BatchNorm
- Label Smoothing

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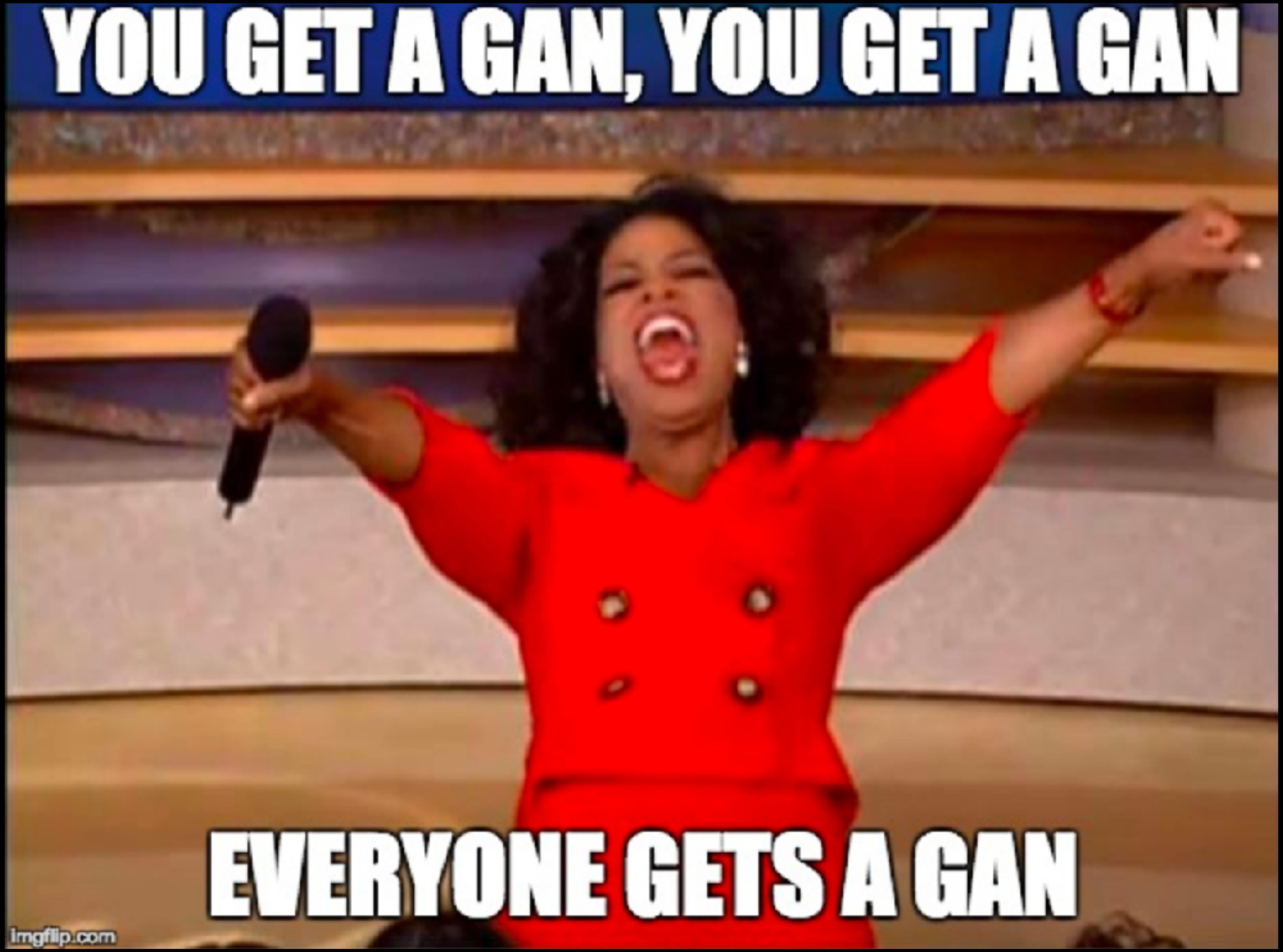
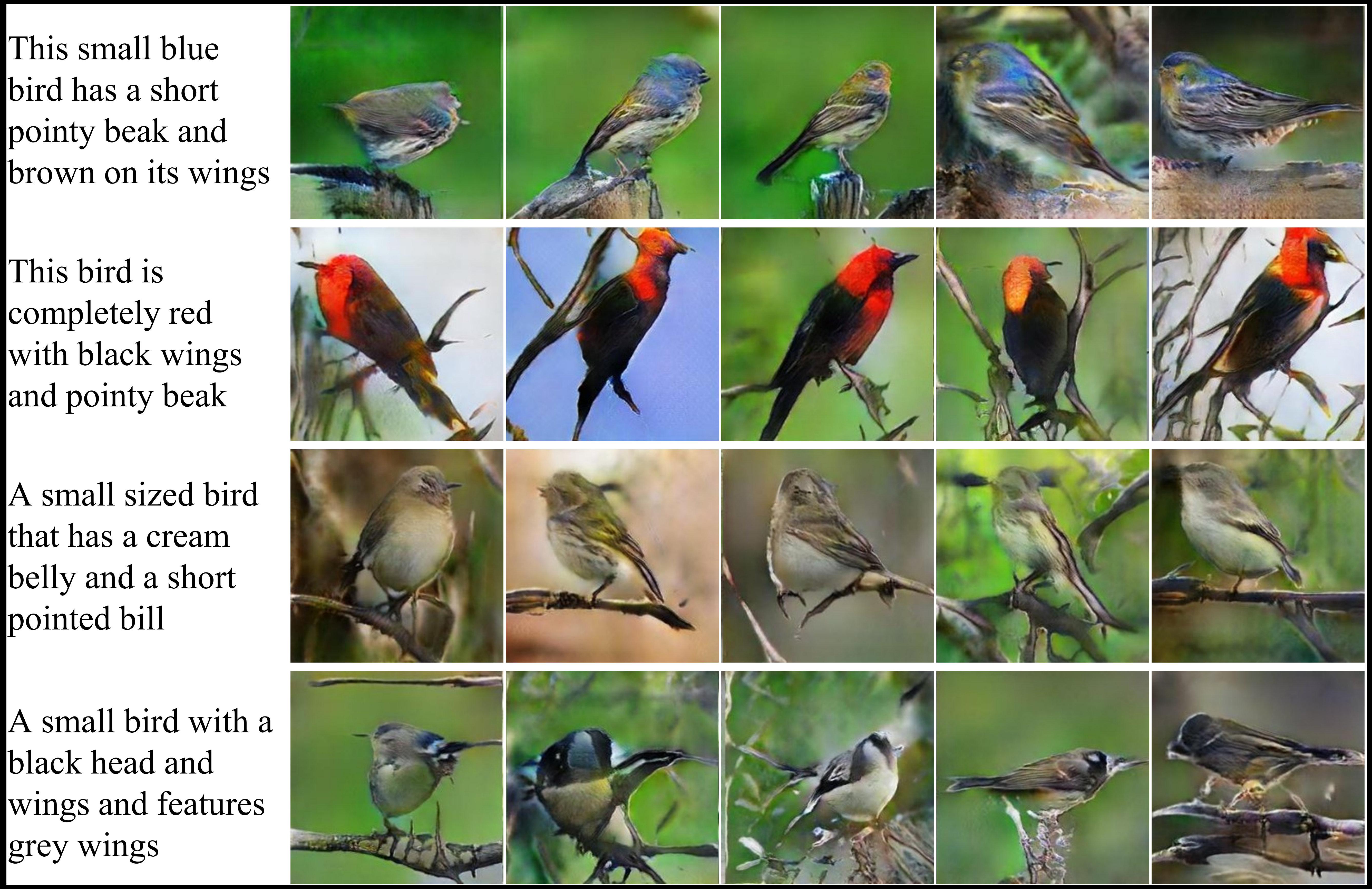
Evaluating GANs

- No simple empirical way to evaluate
- Generally it comes to how good are the pics. (Resolution, blurred/clear, defects in image)
- Can use a tool to check for closest match in the training data

Lots of GANs



StackGANs



(Zhang et al 2016)

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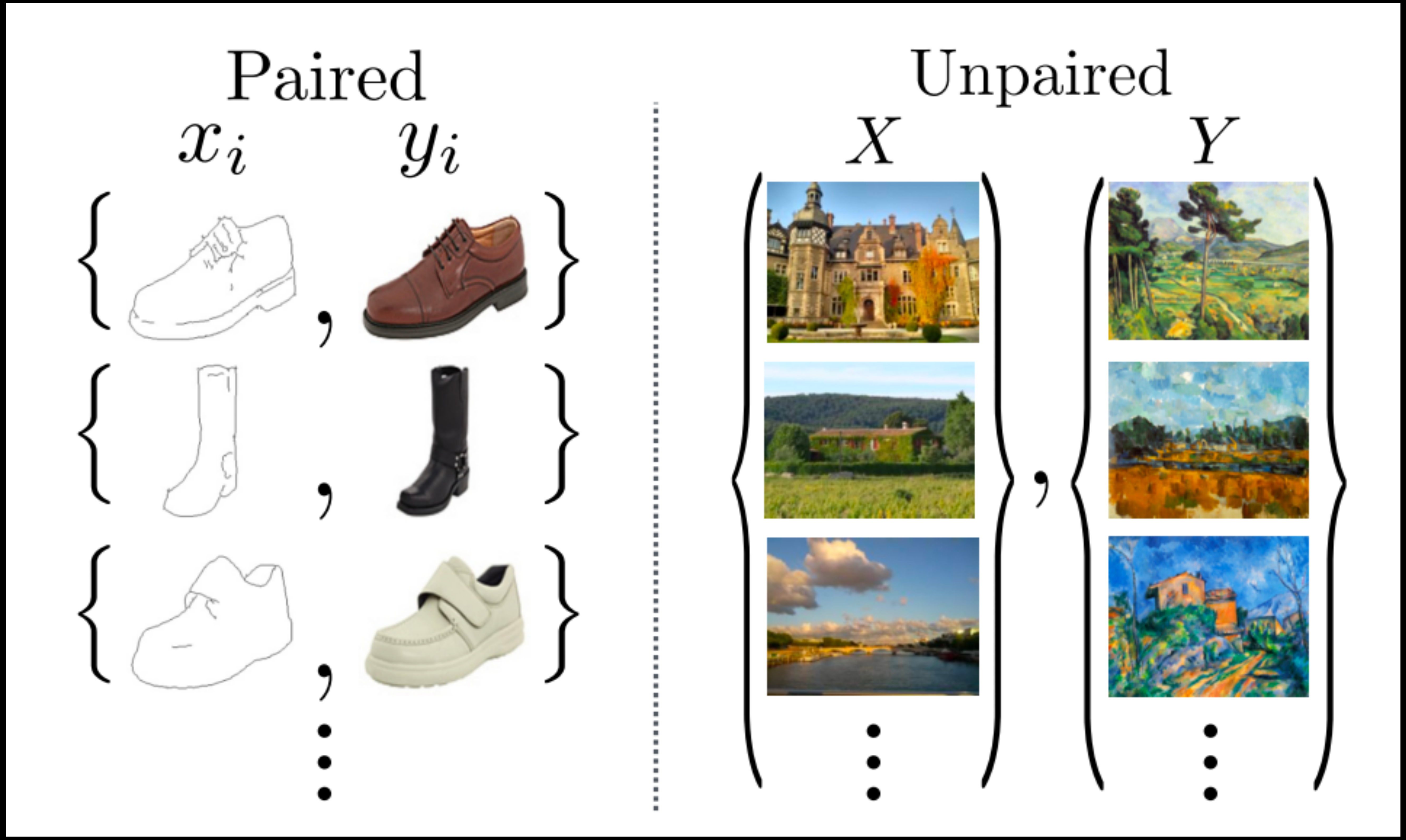
(Goodfellow 2016)

CycleGAN



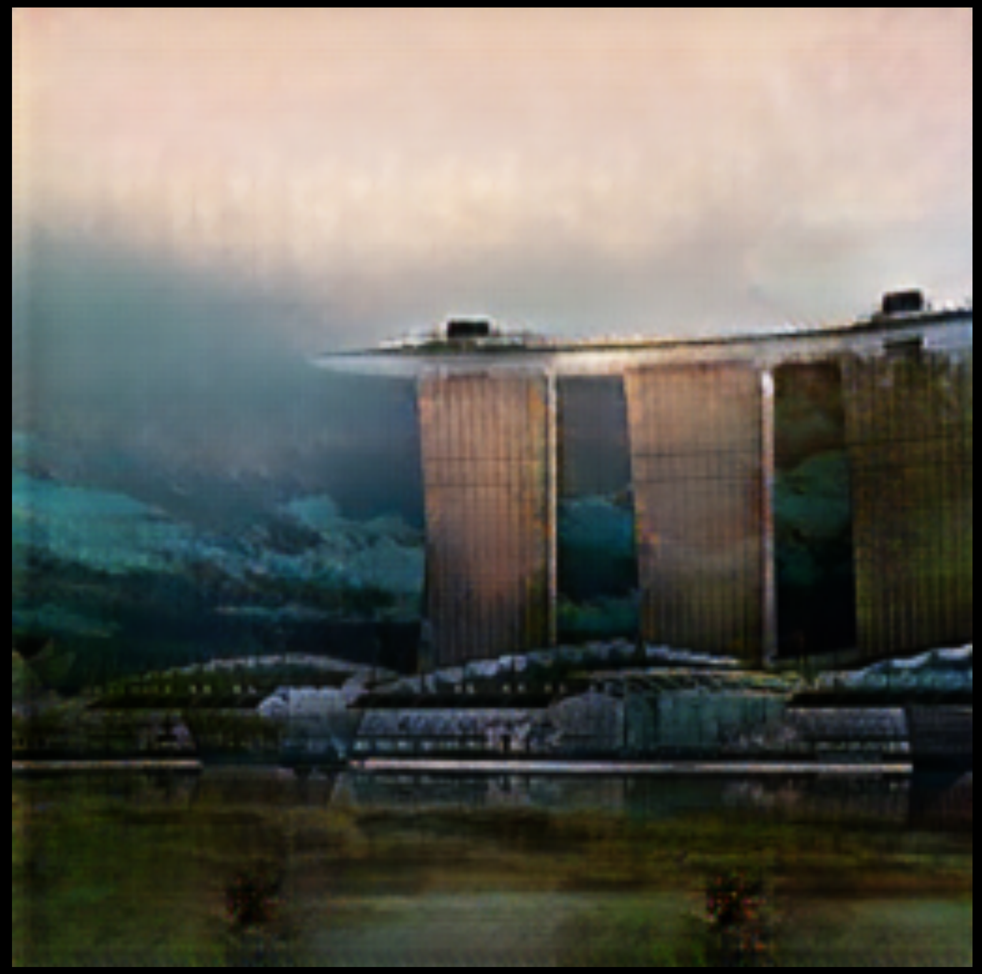
CycleGAN



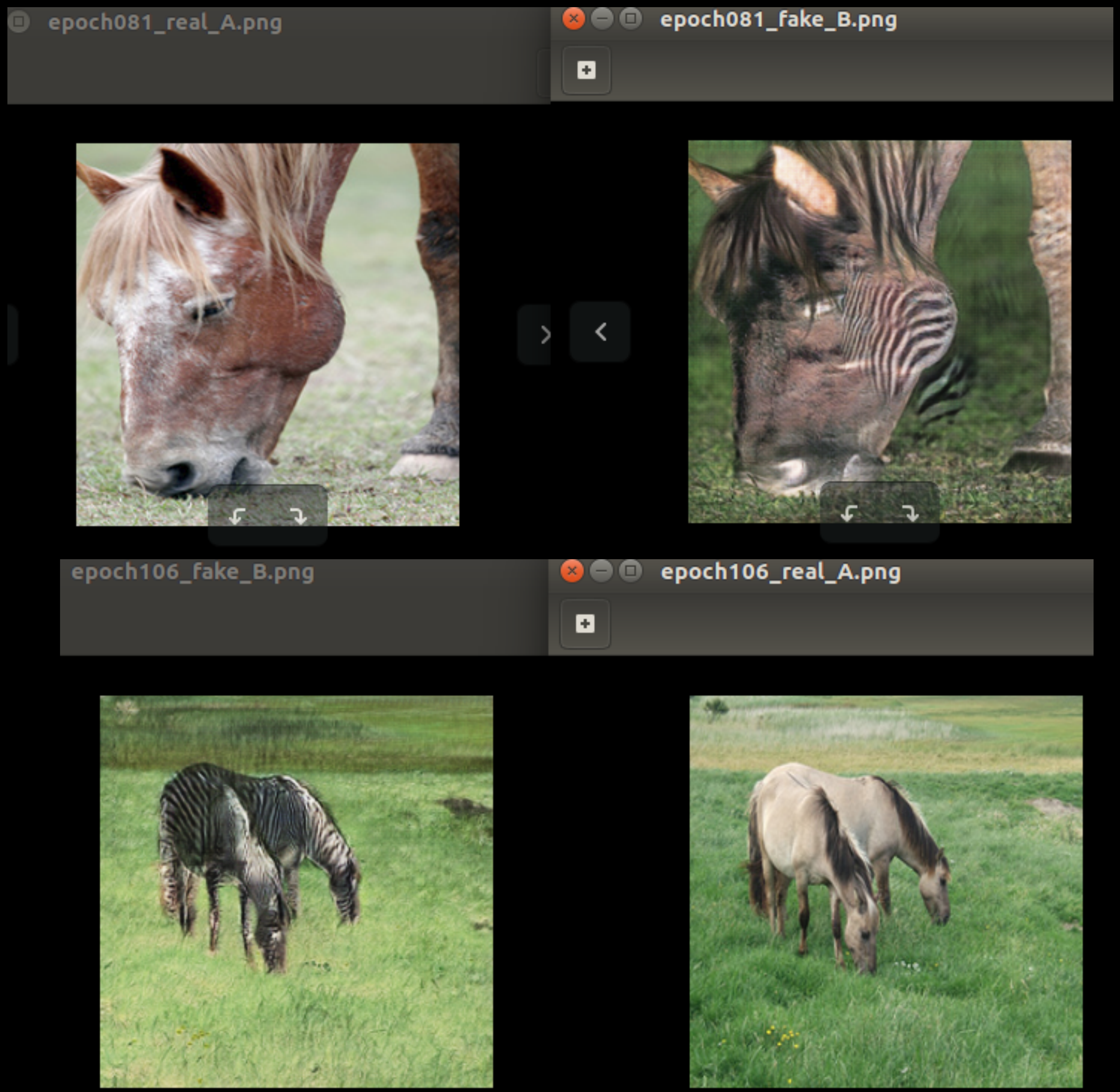

CycleGAN

CycleGAN



CycleGAN


epoch081_real_A.png
epoch081_fake_B.png
epoch106_fake_B.png
epoch106_real_A.png