Generative Adversarial Networks (GANs)

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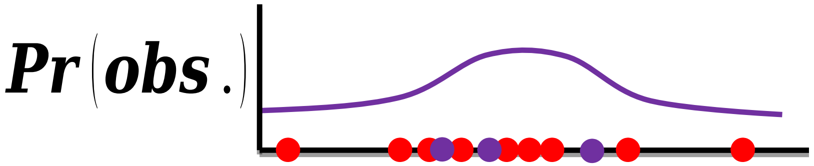
From Dr.Michael Mozer

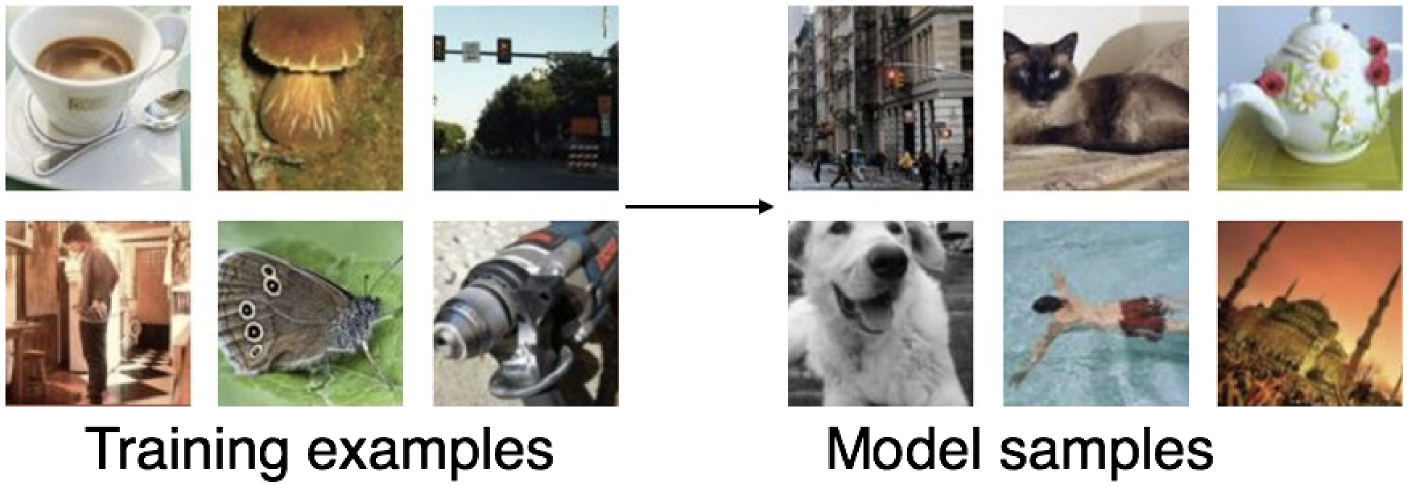
- **Goodfellow, Ian; Pouget-Abadie, Jean; Mirza, Mehdi; Xu, Bing; Warde-Farley, David; Ozair, Sherjil; Courville, Aaron; Bengio, Yoshua (2014). *Generative Adversarial Networks*. Proceedings of the International Conference on Neural Information Processing Systems (NIPS 2014). pp. 2672–2680.**

Probabilistic Generative Models

Density Estimation

Synthesizing Examples
From Probabilistic Generative Model

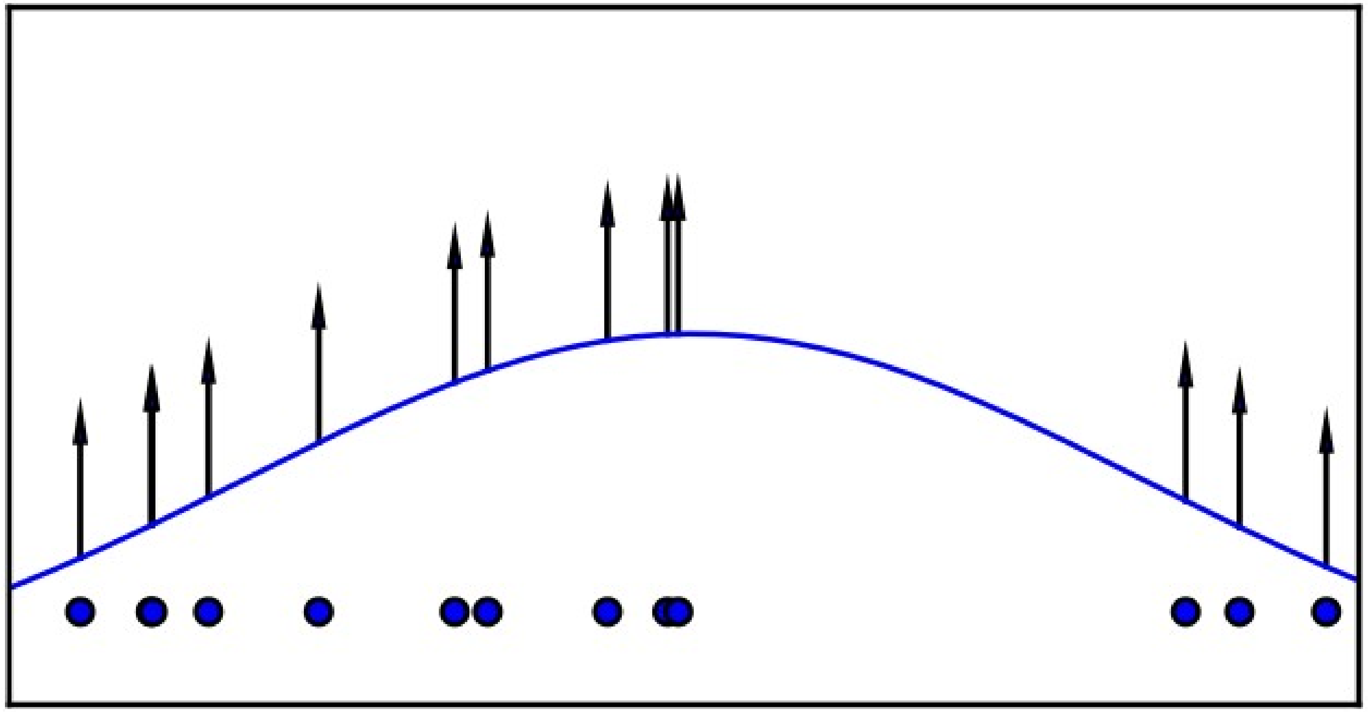




Goodfellow (2017)

Goodfellow NIPS tutorial and accompanying paper (arXiv:1701.00160v4 [cs.LG]) provided some figures

Maximum Likelihood Estimation



$$\boldsymbol{\theta}^* = \arg\max_{\boldsymbol{\theta}} \mathbb{E}_{x\sim p_{\text{data}}} \log p_{\text{model}}(\boldsymbol{x} \mid \boldsymbol{\theta})$$

Goodfellow (2017)

Density function

Explicit and analytical

- e.g., Gaussian
- can sample directly from model

Explicit and approximate

- e.g., Gaussian mixture models, zero-inflated negative binomial models
- can estimate probability by running Markov chain monte carlo

Implicit

- GAN
- can’t estimate probability but can draw from distribution with given probability

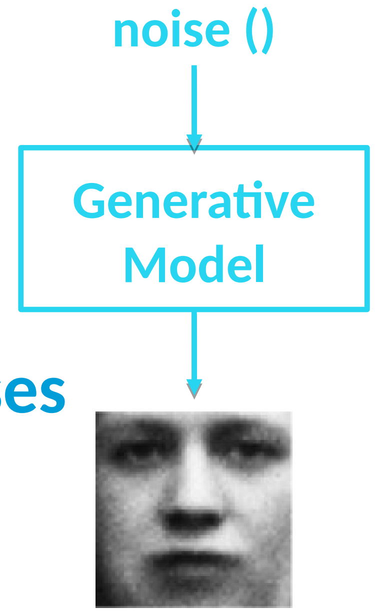
Generative Model

How to make it generate different samples each time it is run?

- input to model is noise

Generative model as a neural network

- Generate random samples by computing a transformation of noises
- differentiable
- does not have to be invertible
- typically has very high dimensionality



Discriminative Model

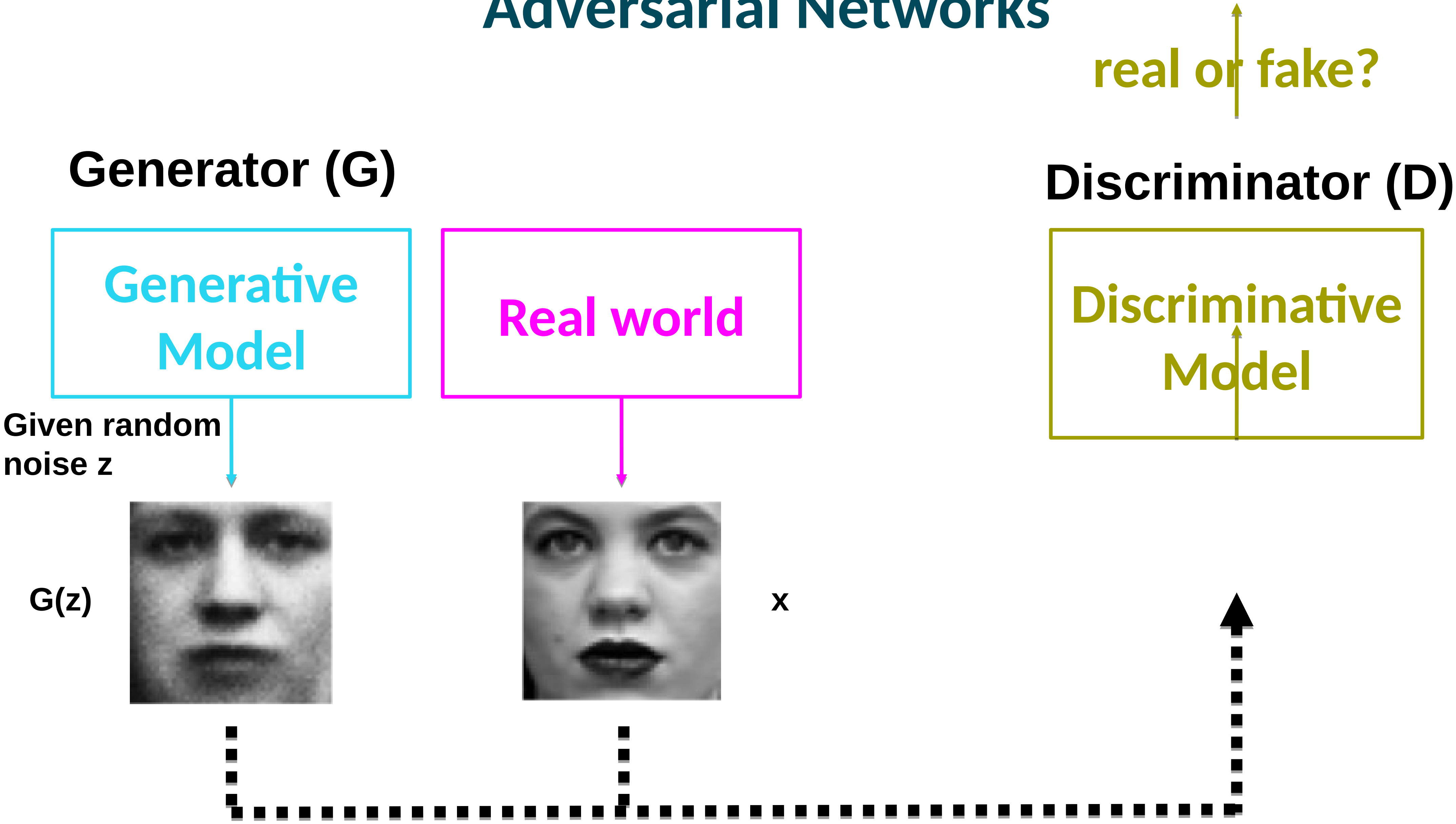
Think of it as a critic

- a good critic can tell real from fake

Discriminative model as a neural net

- differentiable
- computes , with value 1 if real, 0 if fake

Adversarial Networks



Training Procedure: Basic Idea

G tries to fool D

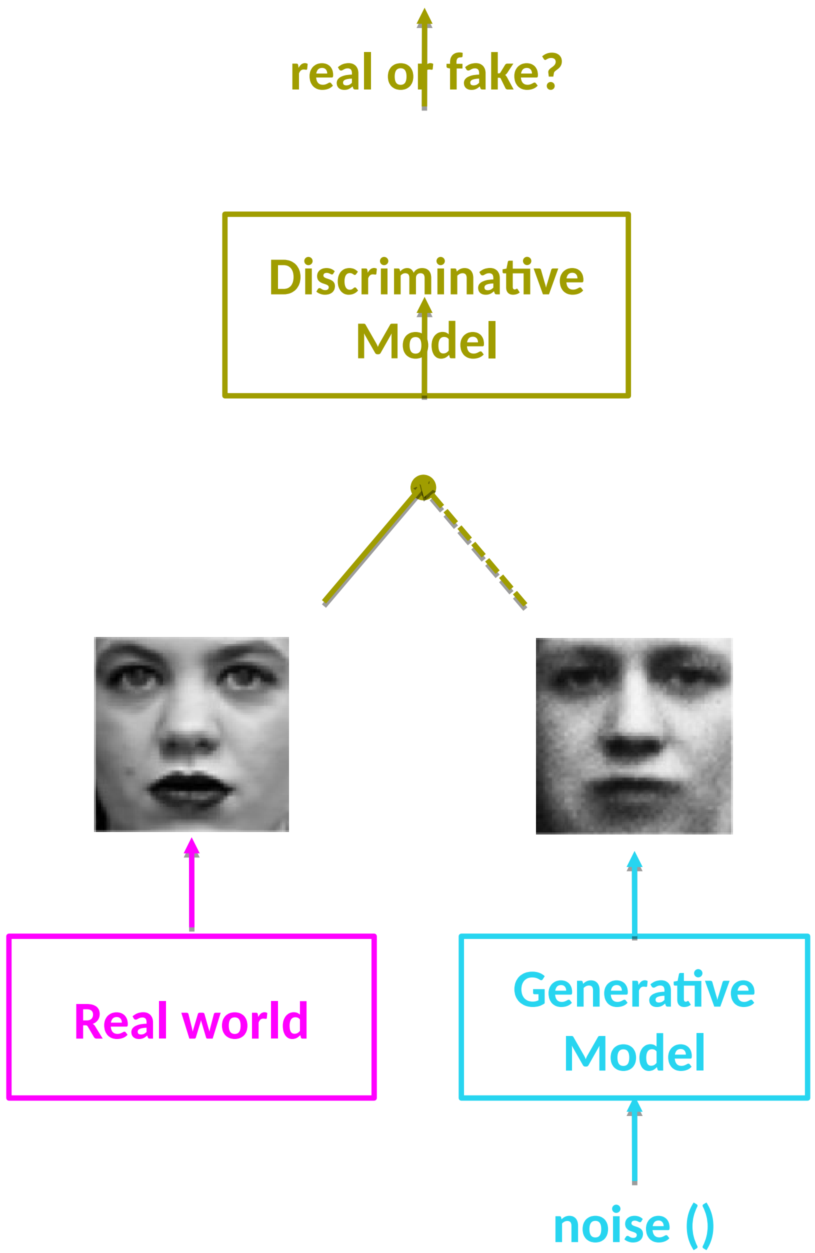
D tries not to be fooled

Models are trained simultaneously

- As G gets better, D has a more challenging task
- As D gets better, G has a more challenging task

Ultimately, we don't care about the D

- Its role is to force G to work harder



Loss Functions

Loss function for D: x is real data, G(z) is generated data

- **maximize the likelihood that model says 'real' to samples from the world and 'fake' to generated samples**

$$\max \log D(x) + \log(1 - D(G(z)))$$

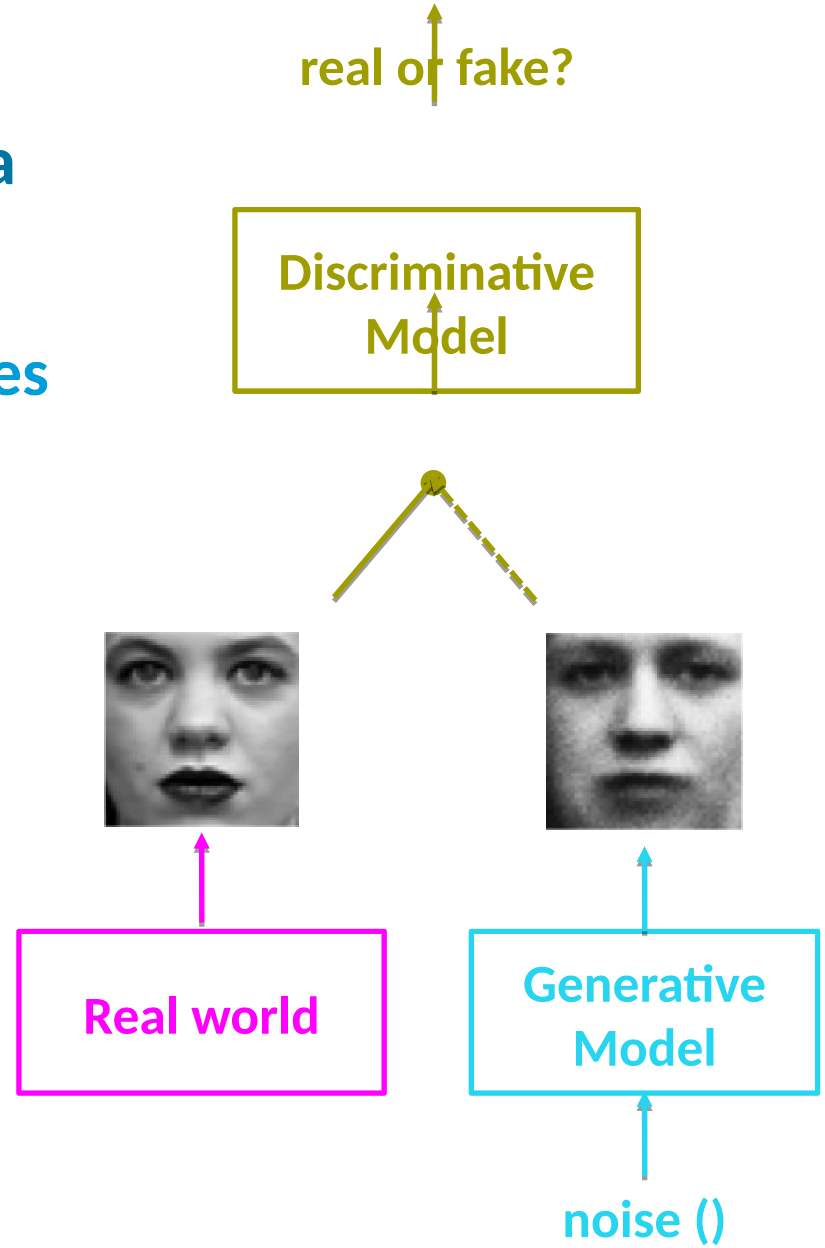
What should the loss function be for G?

$$\min \log D(x) + \log(1 - D(G(z)))$$

But because first term doesn't matter for G (why?),

$$\min \log(1 - D(G(z)))$$

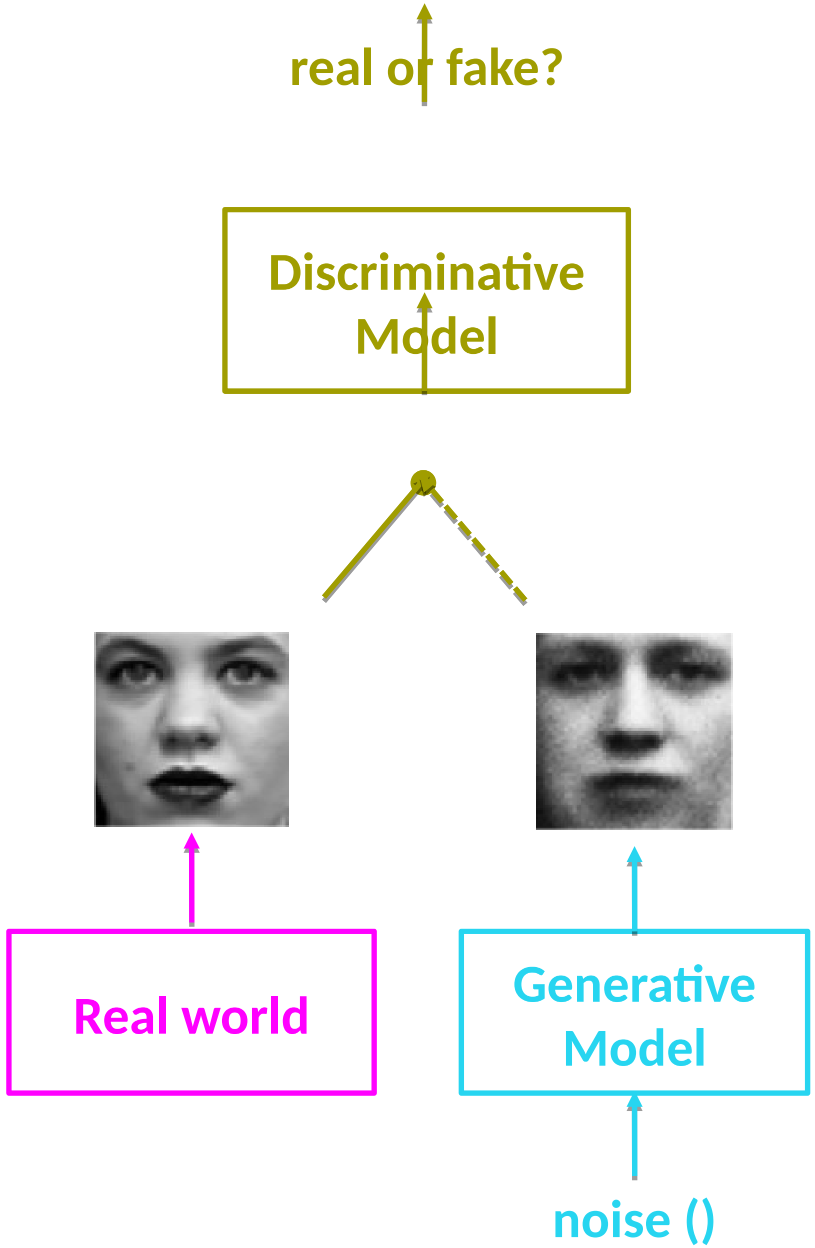
Known as a minimax procedure



Training Procedure

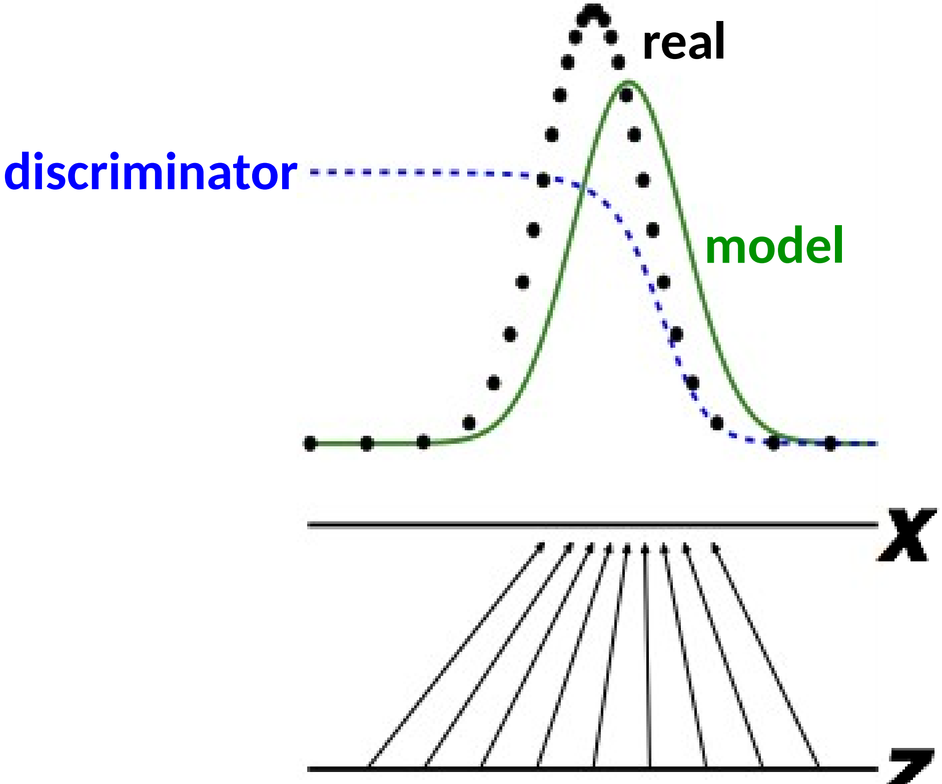
Train both models simultaneously via stochastic gradient descent using minibatches consisting of

- some generated samples
- some real-world samples

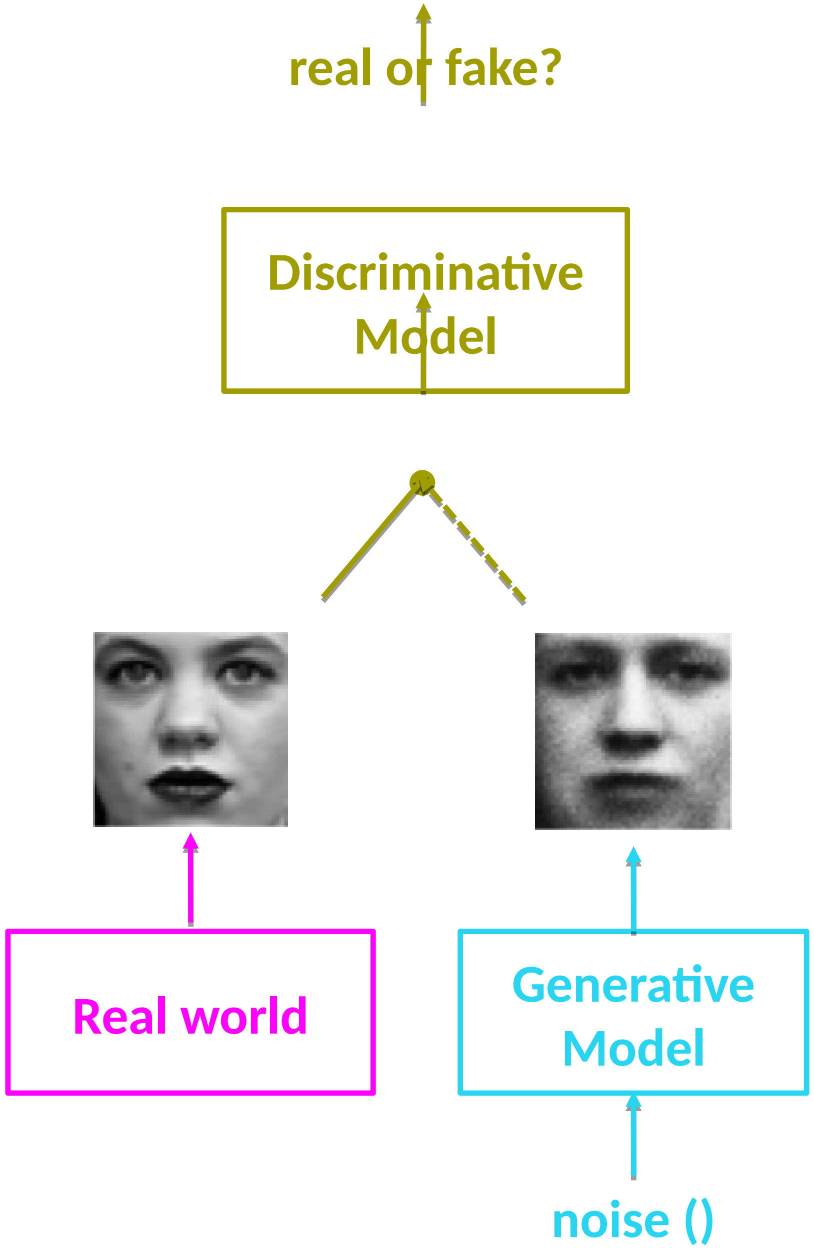


The Discriminator Has a Straightforward Task

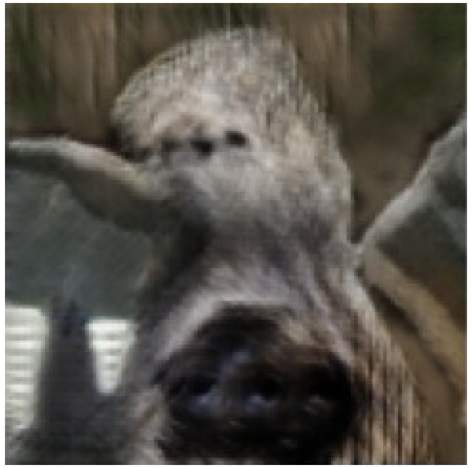
D has learned when

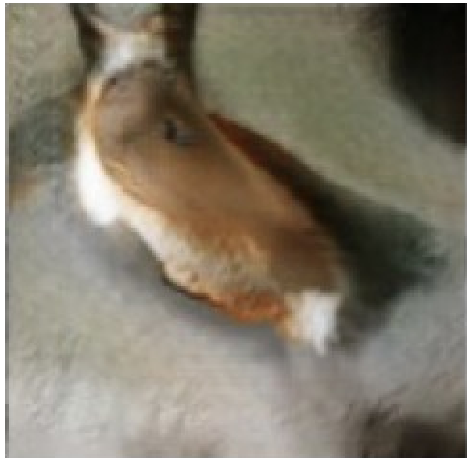


Goodfellow (2017)



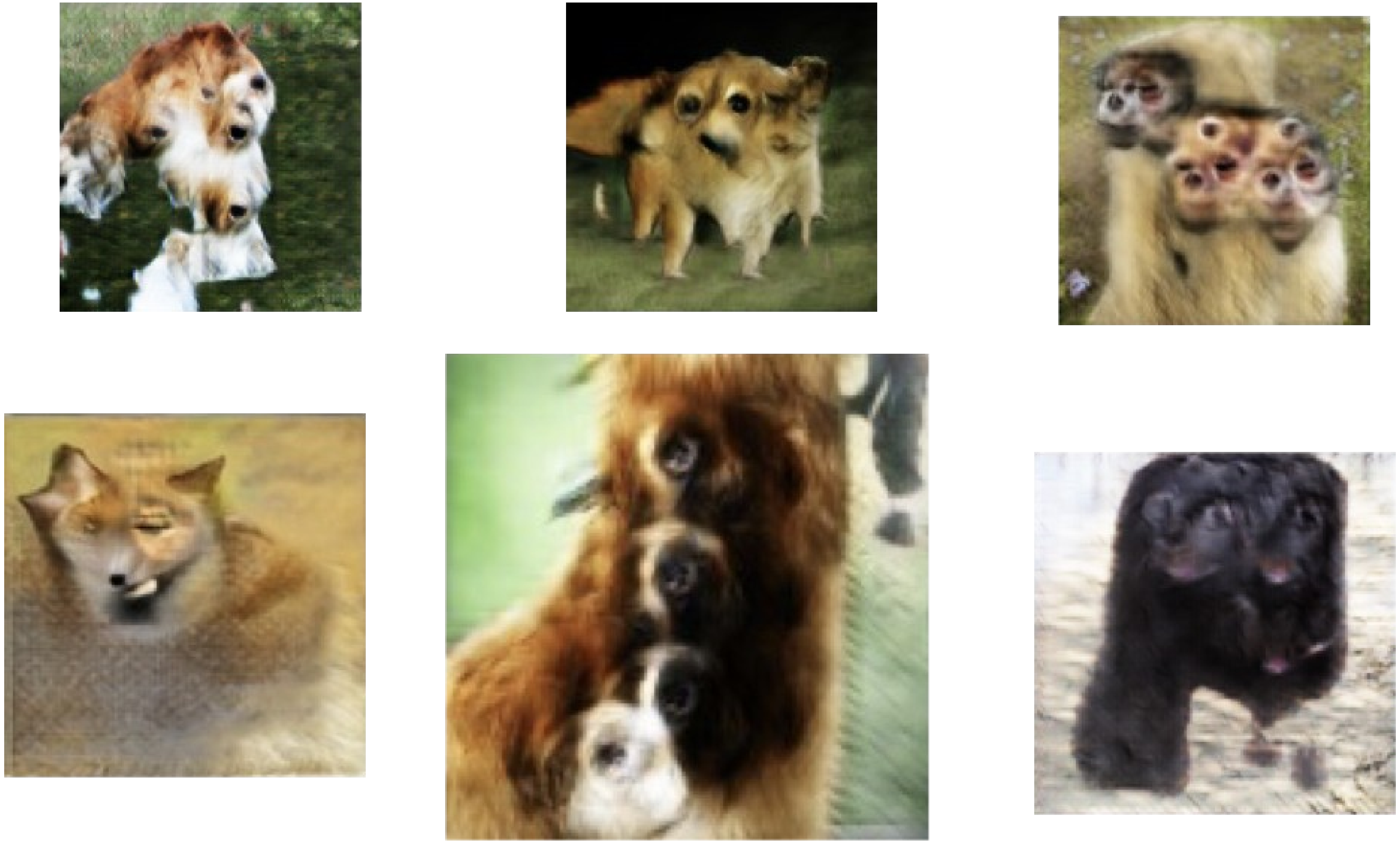
Cherry Picked Results

Goodfellow (2017)

Problems With Counting



Goodfellow (2017)

Problems With Global Structure






Goodfellow (2017)

Visually-Aware Fashion Recommendation and Design With GANs (Kang et al., 2017)

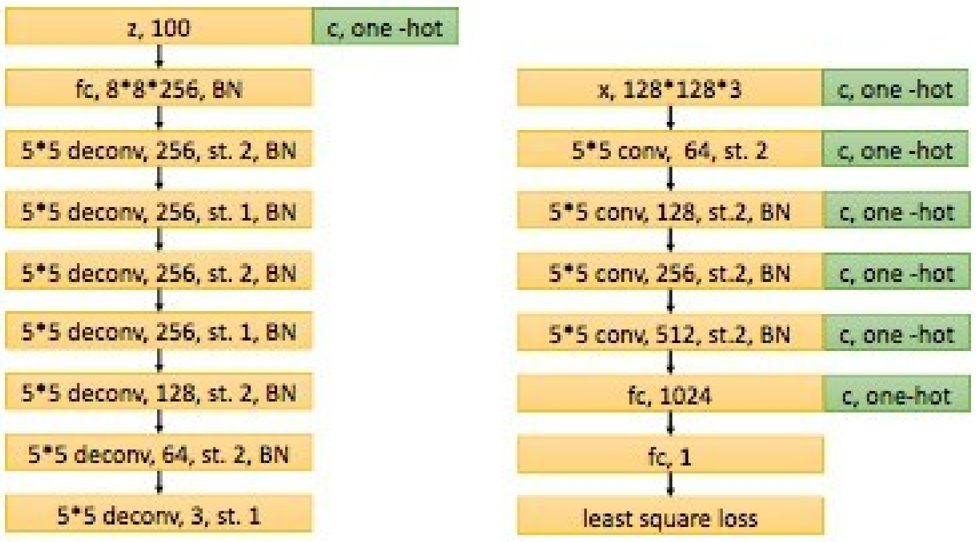
Recommender systems predict how much a particular user will like a particular item

- **Can predict based on features of item (e.g., movie director, dress length)**
- **Can also predict directly from images**

Twist here is that instead of predicting from a predefined set, *generate images* that would be liked.

Visually-Aware Fashion Recommendation and Design With GANs (Kang et al., 2017)

Use class-conditional generator and discriminator



(a) Generator G(z,c)

(b) Discriminator D(x,c)

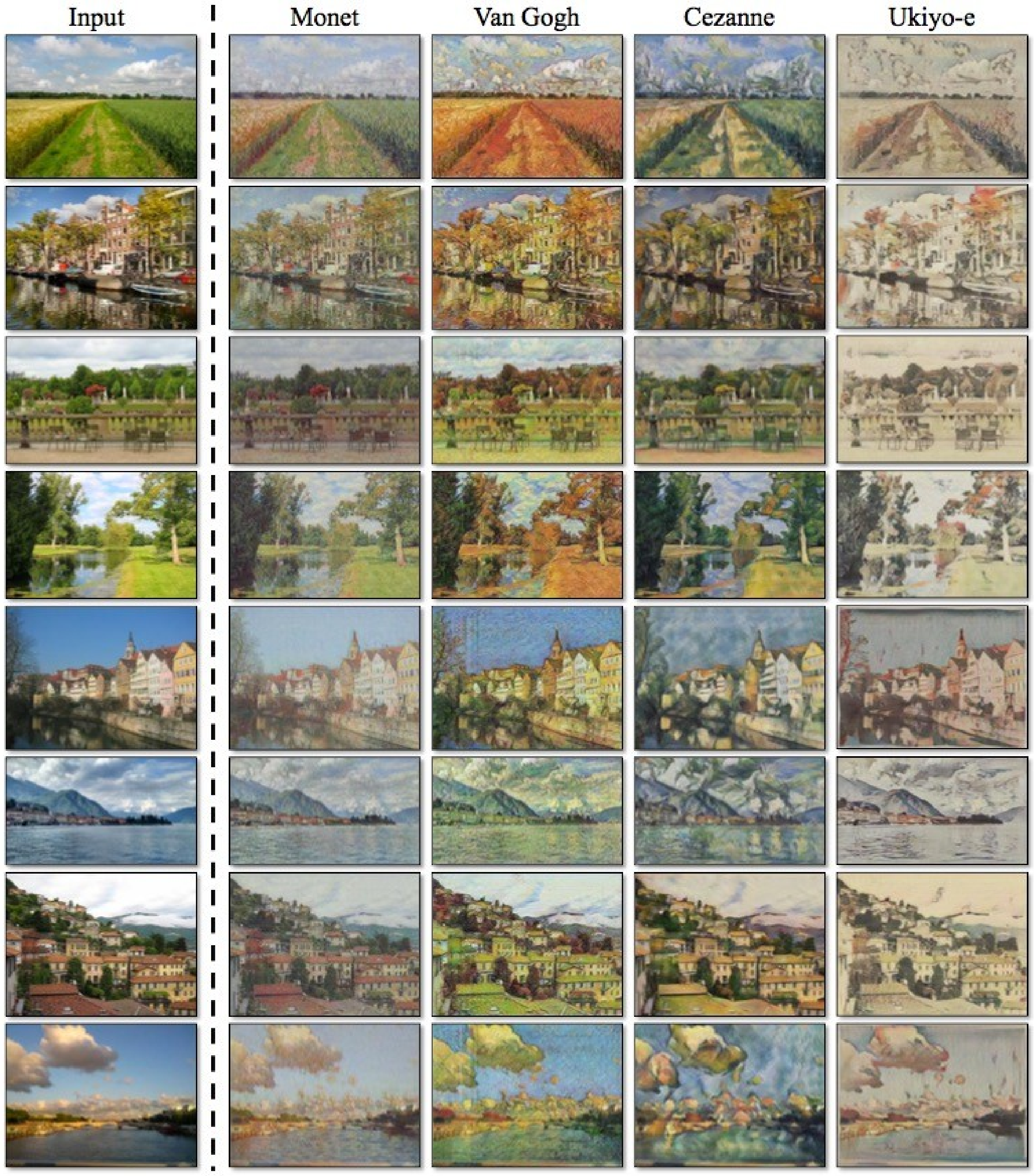
Visually-Aware Fashion Recommendation and Design With GANs (Kang et al., 2017)

Optimize with GAN

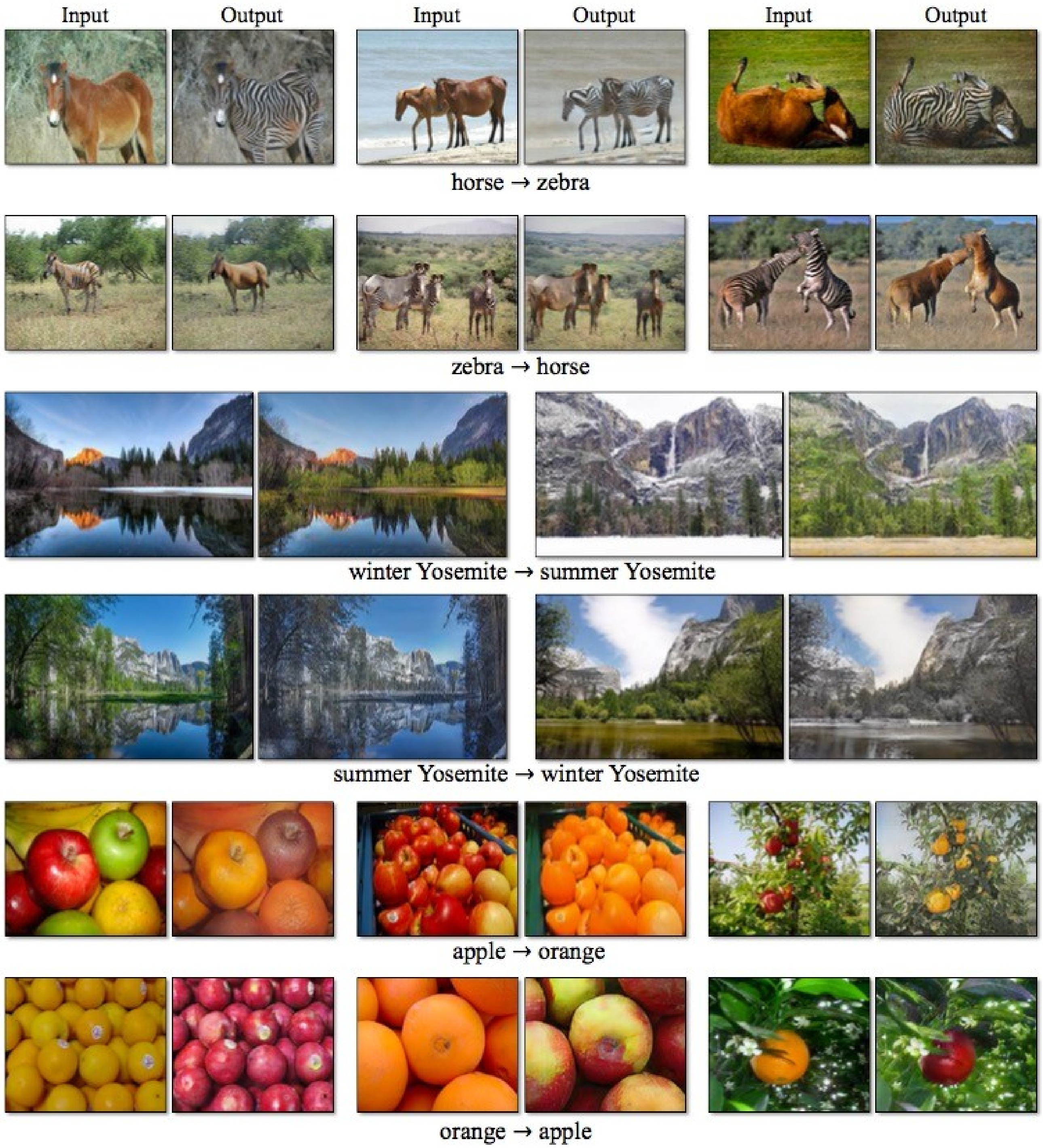
- find latent representation that obtains the highest recommendation score
- gradient ascent search


(a) Top-3 Results from Dataset
(b) Top-3 Results from GAN
12.29 11.79 11.76 12.89 12.56 12.67
8.07 8.06 7.81 8.14 8.00 7.37
7.07 6.78 6.70 9.49 9.34 8.56
13.28 12.75 12.51 15.05 13.93 13.74
4.27 4.21 4.20 5.37 5.20 4.46
10.28 10.27 10.15 12.67 11.87 10.94

Photos
to paintings



Paintings to photos


Input
Output
Input
Output
Input
Output
horse → zebra
zebra → horse
winter Yosemite → summer Yosemite
summer Yosemite → winter Yosemite
apple → orange
orange → apple

High resolution image synthesis

Large Scale GAN Training for High Fidelity Natural Image Synthesis

2018