PMI Lab
Pattern Recognition and
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Generative Adversarial Networks (GANs)

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Introduction and Background

Generative Model (1/3)

- Generative adversarial networks are an example of **generative models**

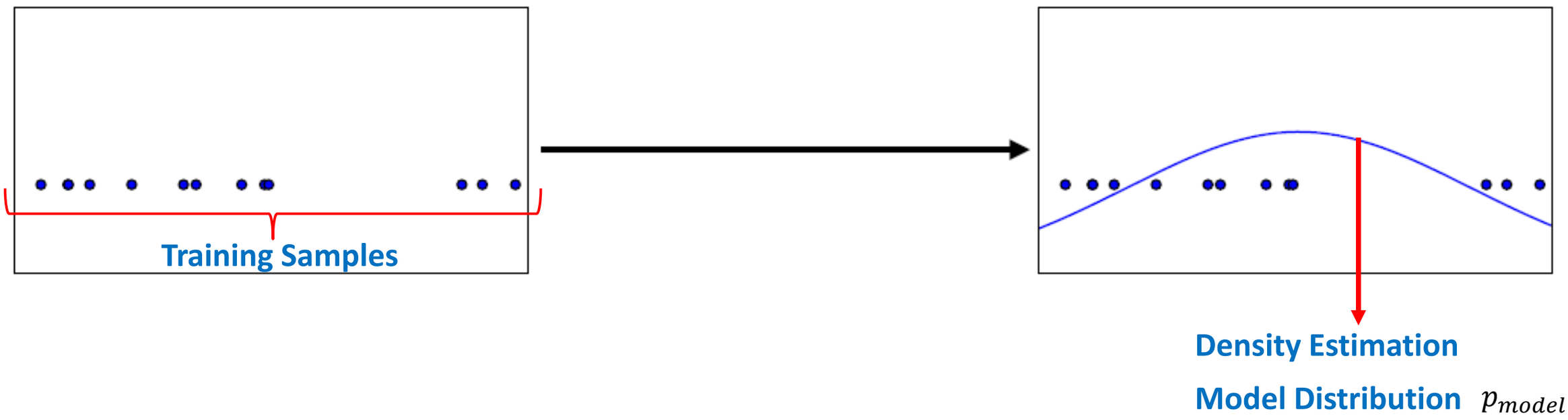
- This refers to any model that takes a training set, consisting of samples drawn from a distribution p_{data} and learns to represent an estimate of distribution

→ **Density Estimation**

- GANs focus primarily on **sample generation**

Generative Model (2/3)

❖ Example of Density Estimation



- A training set of examples drawn from an unknown data-generating distribution p_{data}
- Estimate of distribution p_{data}
- The estimate p_{model} can be evaluated for a particular value of x to obtain an estimate $p_{model}(x)$ of the true density $p_{model}(x)$.

Generative Model (3/3)

- Example of Sample Generation

Training Examples **Model Samples**

- Generation of samples form the model distribution
- Illustration of samples from the ImageNet dataset
- Generative model would be able to train on examples on the left and then create examples from the same distribution on the right

Why study generative models?

- Excellent test of our ability to use high-dimensional, complicated probability distributions
- Missing data
  - Semi-supervised learning
  - Realistic generation tasks
- Sampling (or generation) is straightforward
- Training doesn't involve maximum likelihood estimation
- Robust to overfitting since the generator never sees the training data
- GANs are good at capturing the modes of distribution

Discriminative vs. Generative Models

❖ Discriminative models

- A discriminative model learns the conditional probability distribution p(y|x) which could be interpreted as the probability of y given x

- Classifier learns by observing data. It makes fewer assumptions on the distributions, but depends heavily on the quality of the data. The distribution p(y|x) simply classifies a given example x directly int a label y.

Discriminative vs. Generative Models

❖ Generative models (1/2)

- Whereas a generative model learns the joint probability distribution p(x,y), where x is the input data and y is the label that you want to classify

- A generative model can generate more samples by itself artificially, based on assumptions about the distribution of data

- For example, in the Naïve Bayes' model, we can learn p(x) from data, also p(y), the prior class probabilities, and we can also learn p(x|y) from the data using say maximum likelihood

$$\arg\max p(x|y)p(y)$$

Discriminative vs. Generative Models

❖ Generative models (2/2)

$$\arg\max p(x|y)p(y)$$

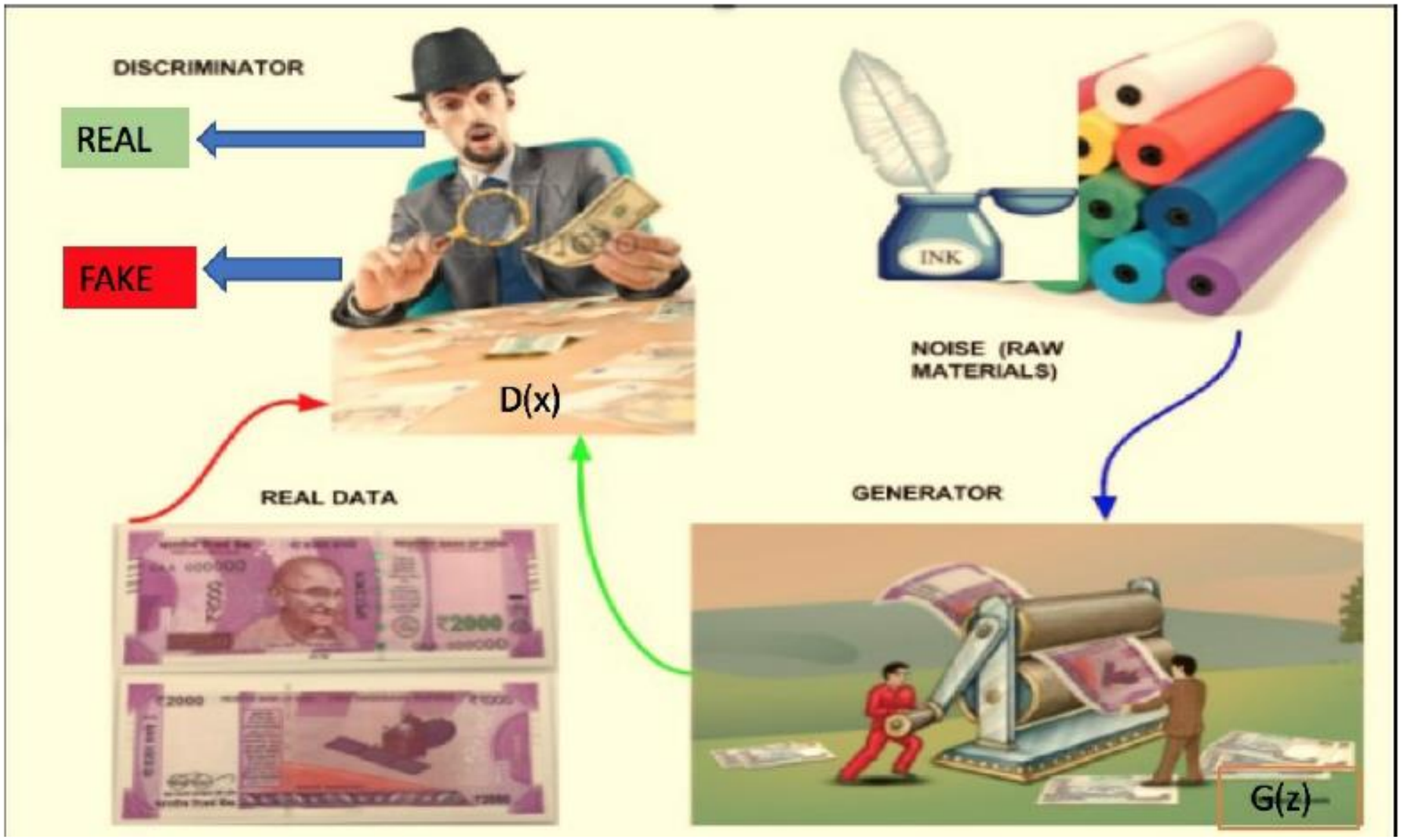
- This is the equation we use in generative models, as $p(x, y) = p(x|y)p(y)$, which explicitly models the actual distribution of each class

- In practice, the discriminative models generally outperform generative models in classification tasks, but the generative model shines over discriminative models in generation task

Adversarial Process

- This can be modeled as a **minimax game** in game theory. This phenomenon is called **adversarial process**
- GAN, introduced by Ian Goodfellow in 2014 at arXiv: 1406.2661, is a special case of an adversarial process where **two neural networks compete against each other**
- The first network generates data and the second network tries to find the difference between the real data and the fake data generated by the first network
- The second network will output a scalar [0,1], which represents a probability of real data

Adversarial Process: Real World Analogy



Police
Discriminator D(x)

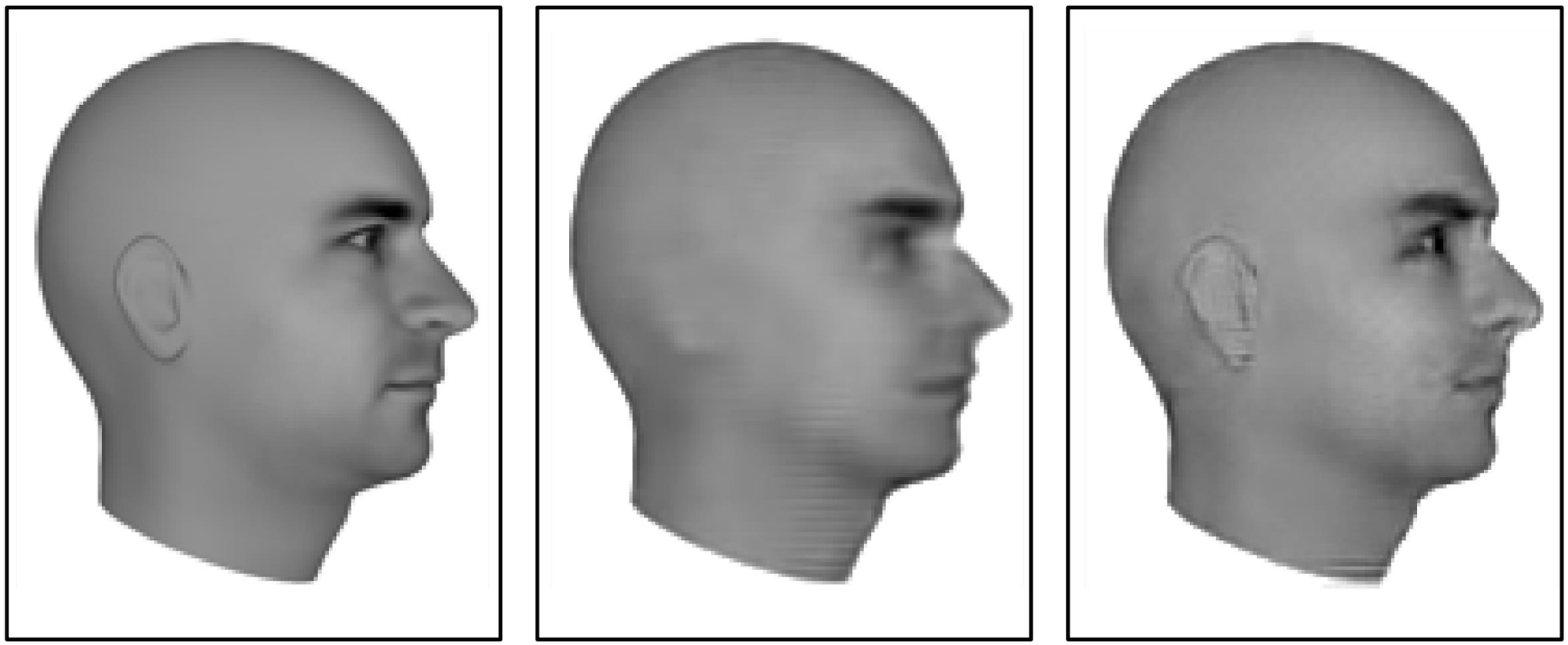
Counterfeiter
Generator G(z)

- To become a successful money counterfeiter, the criminal needs to fool the police so that the police can't tell the difference between fake and real money
- As a paragon of justice, the police want to defect fake money as effectively as possible

Applications

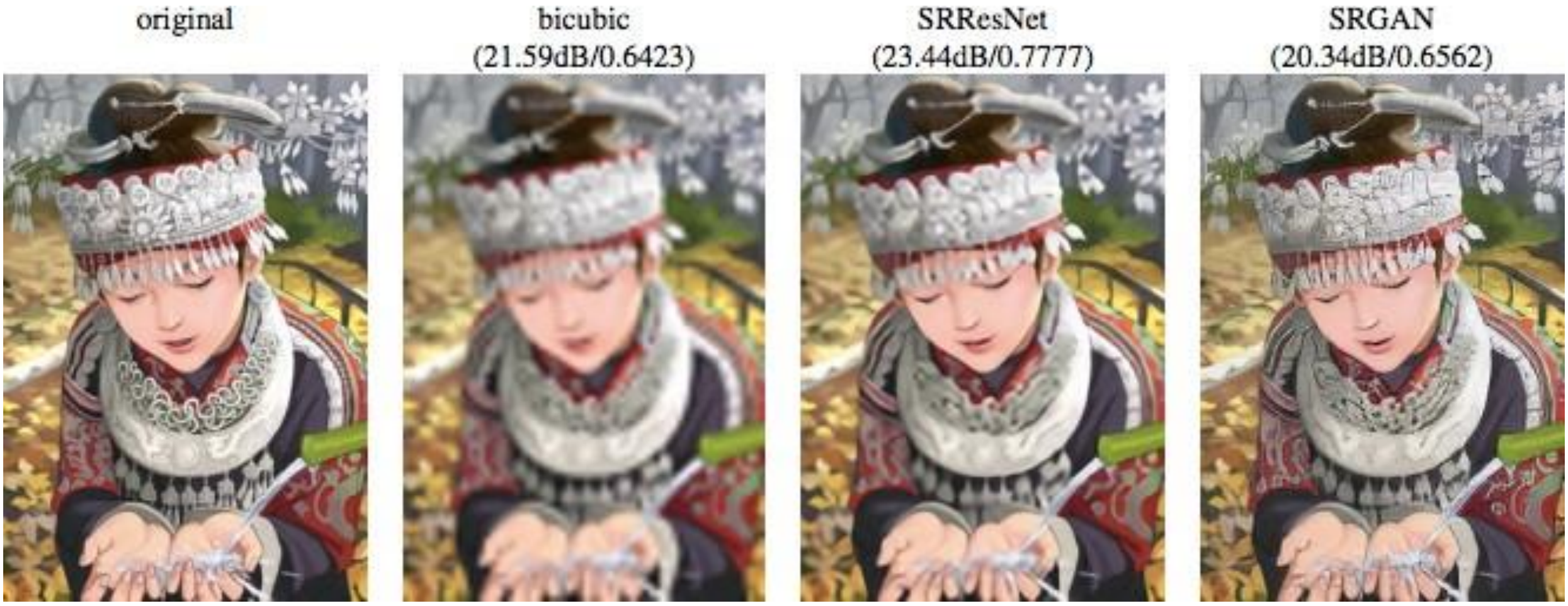
Next Video Frame Prediction

Ground Truth | MSE | Adversarial



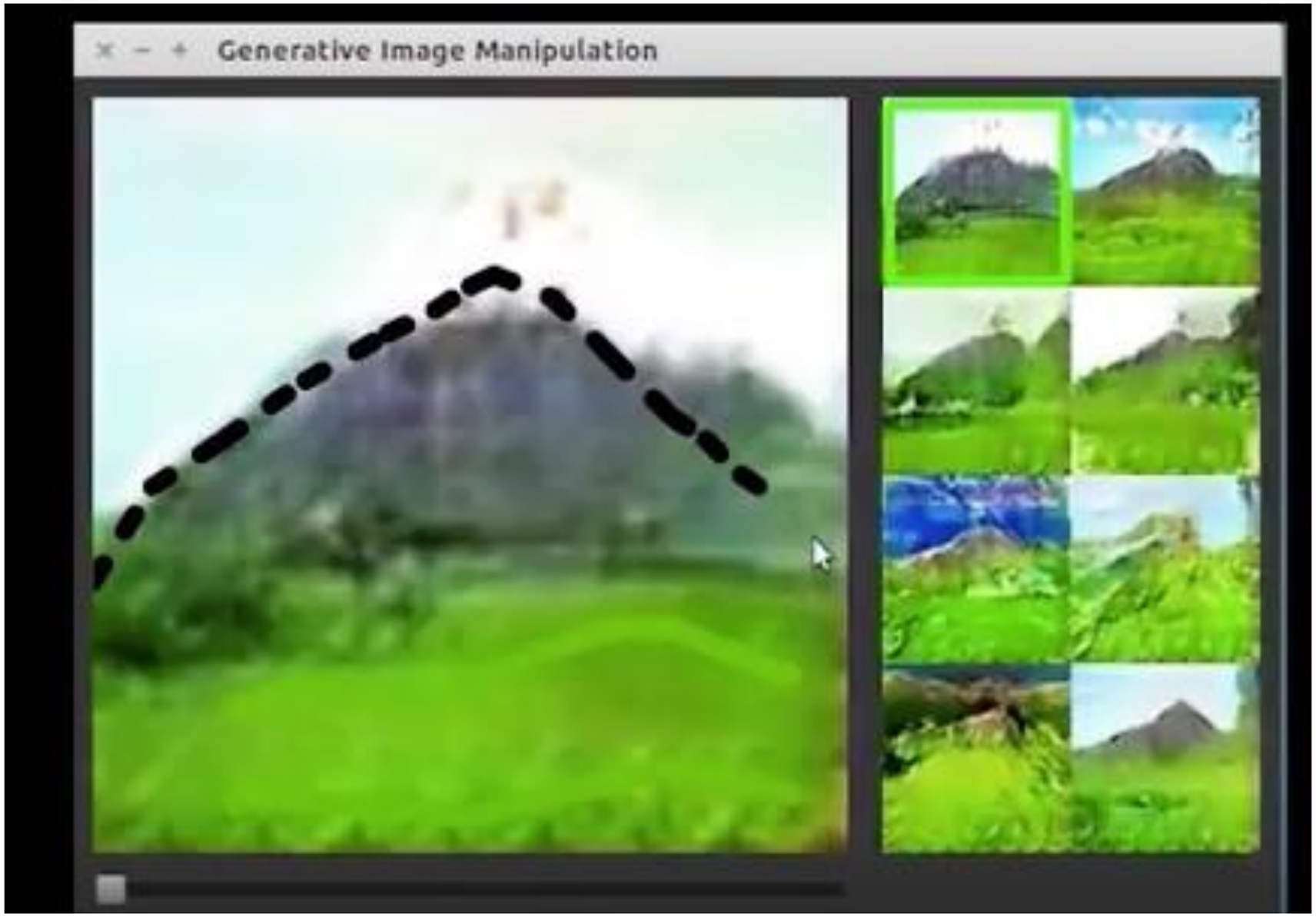
(Ledig et al 2016)

Single Image Super-Resolution



(Ledig et al 2016)

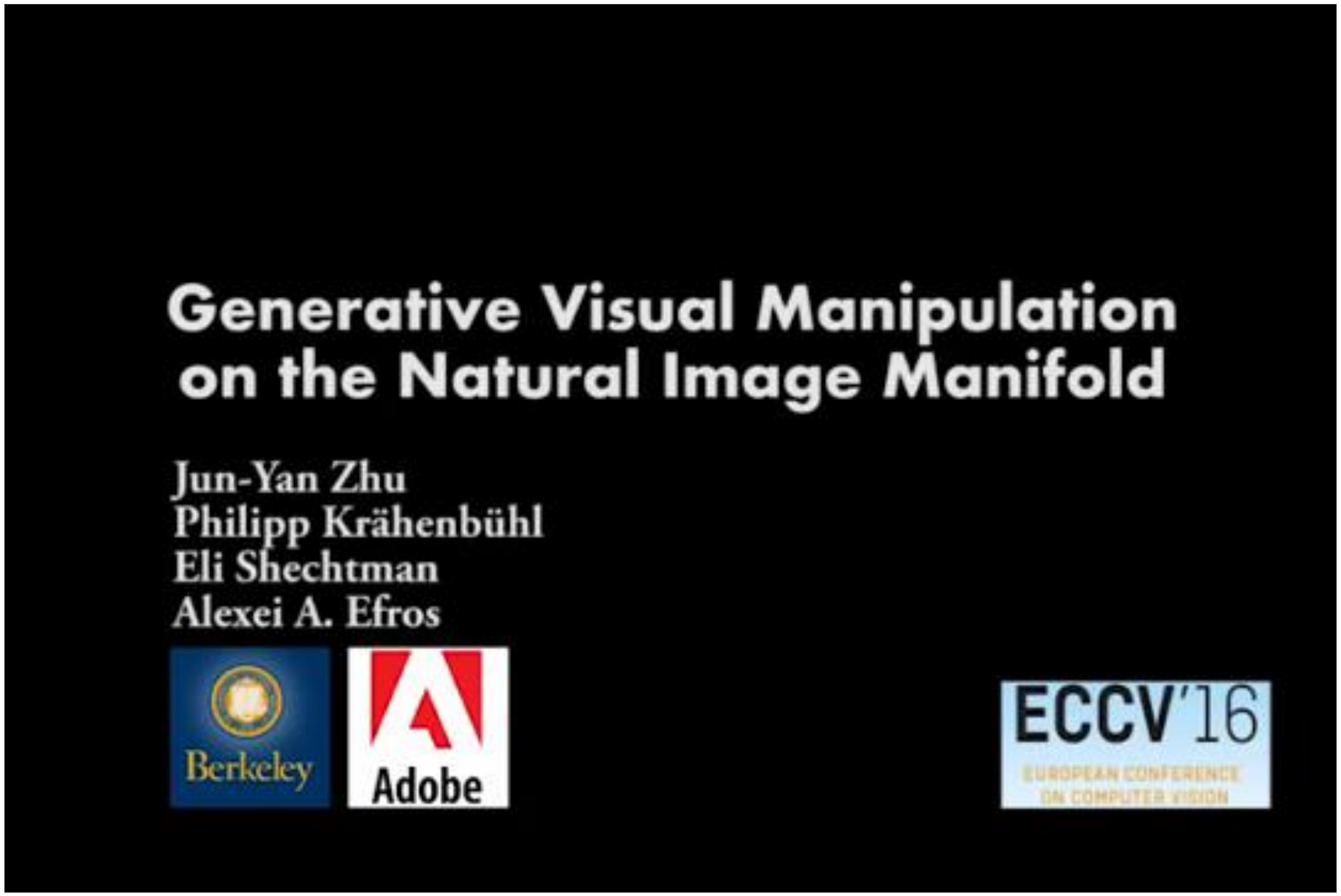
iGAN



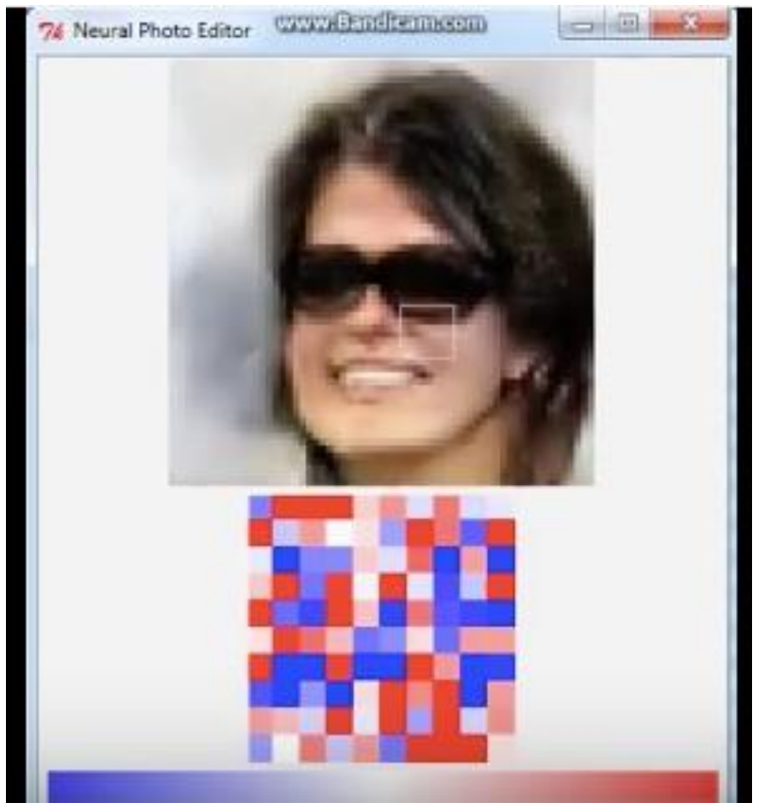
youtube

(Zhu et al 2016)

iGAN


Generative Visual Manipulation
on the Natural Image Manifold
Jun-Yan Zhu
Philipp Krähenbühl
Eli Shechtman
Alexei A. Efros
Berkeley
Adobe
ECCV'16
EUROPEAN CONFERENCE
ON COMPUTER VISION

Introspective Adversarial Networks



youtube

(Brock et al 2016)

Introspective Adversarial Networks

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Neural Photo Editing

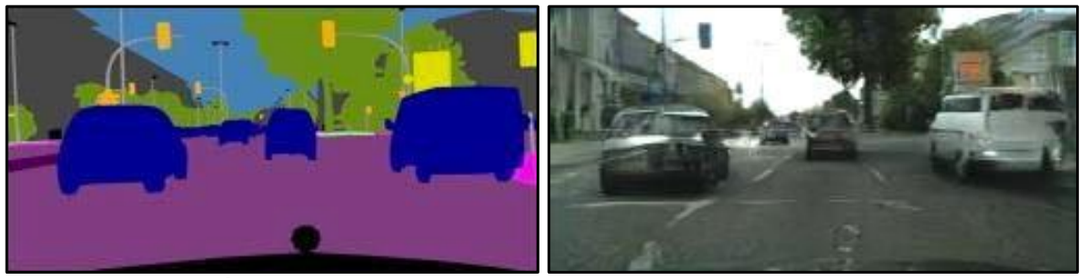
Andrew Brock

EDINBURGH CENTRE FOR ROBOTICS
Innovation Ready

[redacted]

Image to Image Translation

Labels to Street Scene



input output

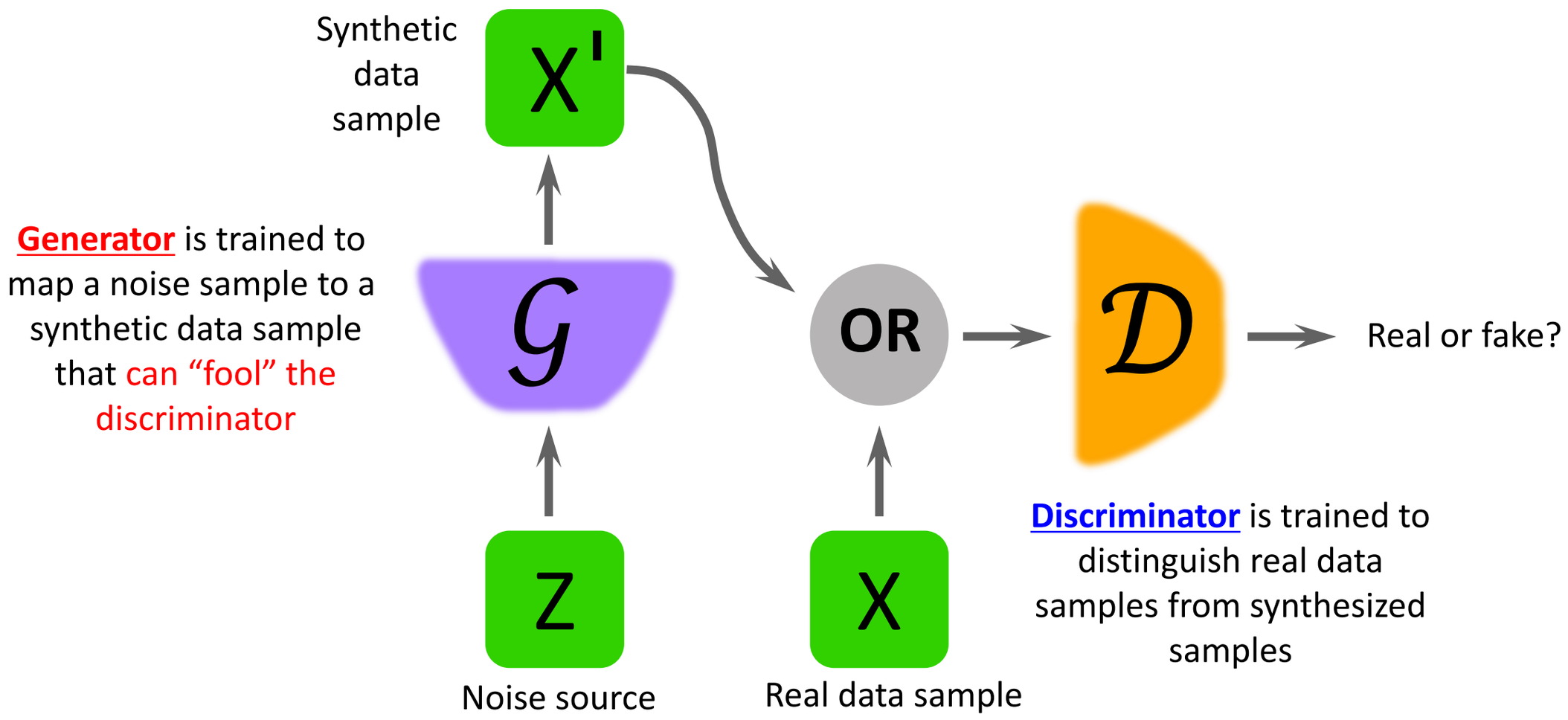
Aerial to Map

input output

(Isola et al 2016)

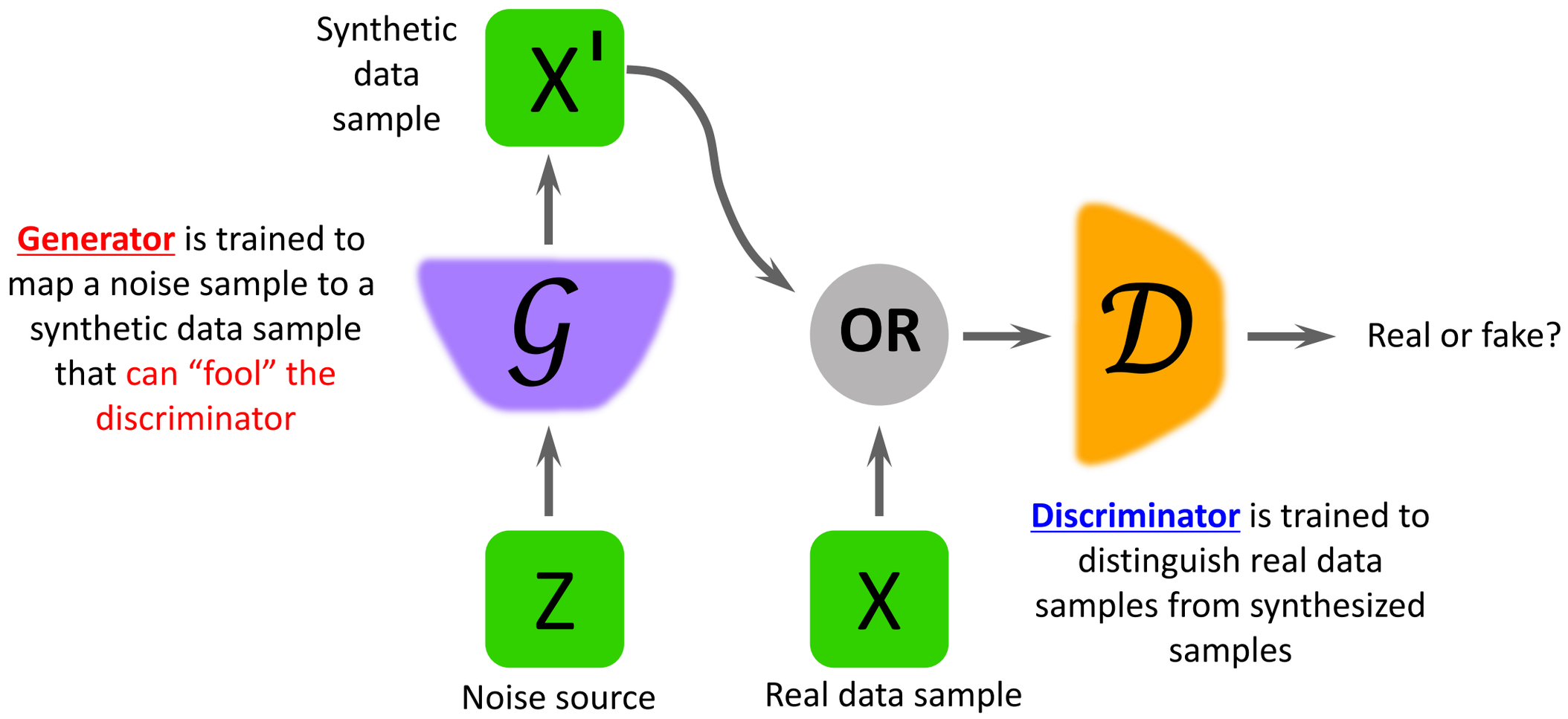
Generative Adversarial Networks (GANs)

Overview of GAN (1/5)



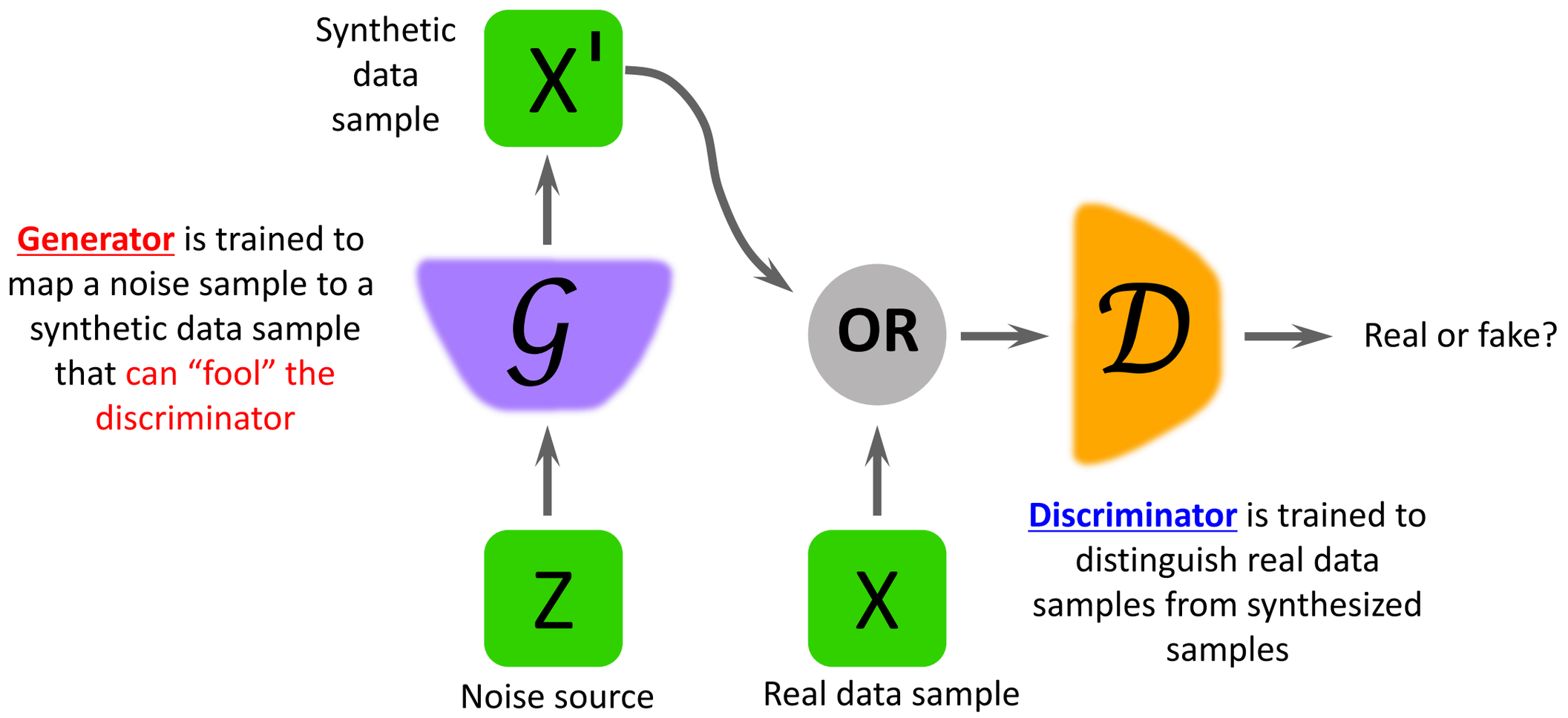
- The forger, known in the GAN literature as the generator, $\mathcal{G}$, creates forgeries, with the aim of making realistic images
- The expert, known as the discriminator, $\mathcal{D}$, receives both forgeries and real images, and aims to tell them apart
- Both are trained simultaneously, and in competition with each other

Overview of GAN (2/5)



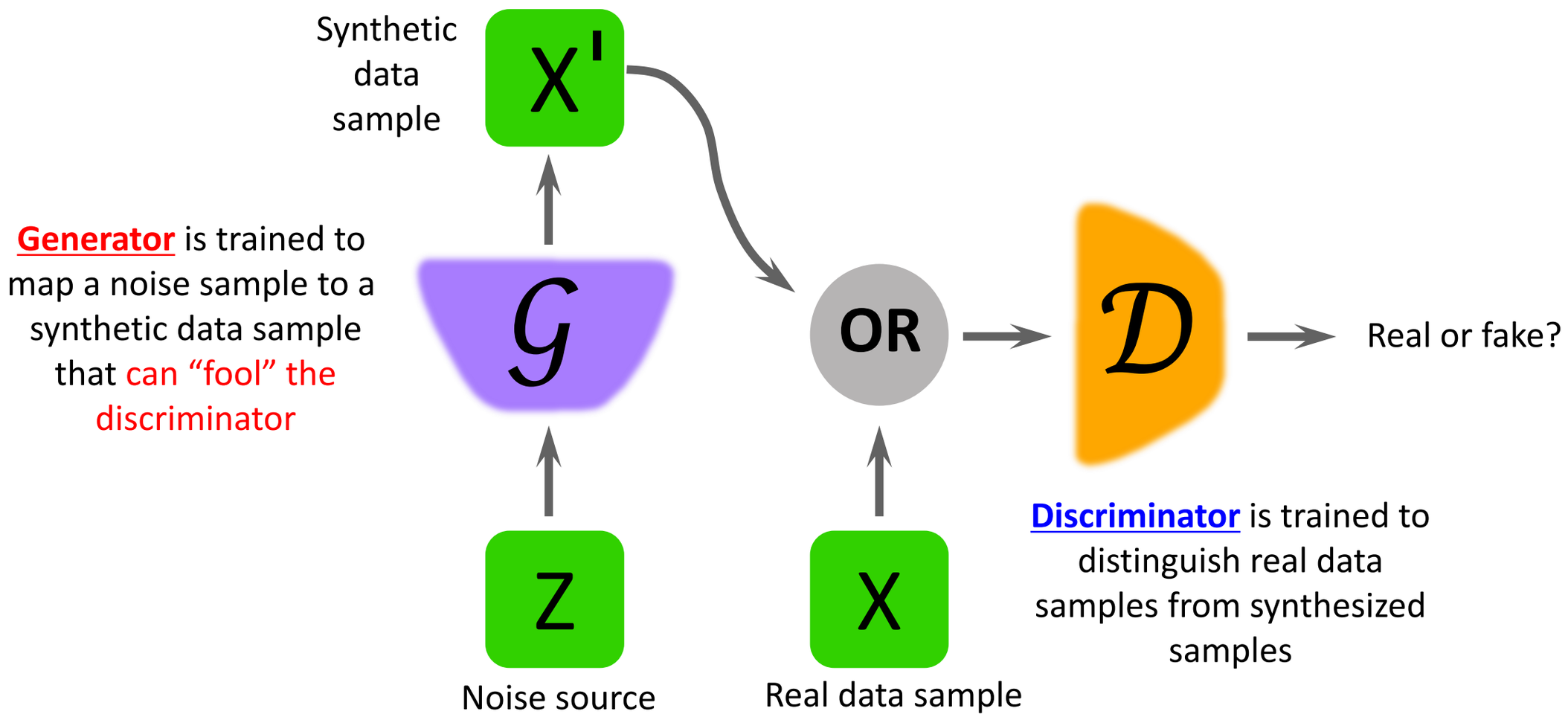
- Crucially, Generator has no direct access to real images – the only way it learns is through its interaction with the discriminator
- Discriminator has access to both the synthetic samples and samples drawn from the stack of real images

Overview of GAN (3/5)



We express generator formally as $\mathcal{G}: \mathcal{G}(\mathrm{z}) \rightarrow R^{|\mathrm{x}|}$, where $\mathrm{z} \in R^{|\mathrm{z}|}$ is a sample from the latent space, $\mathrm{x} \in R^{|\mathrm{x}|}$ is an image and $|\cdot|$ denotes the number of dimensions

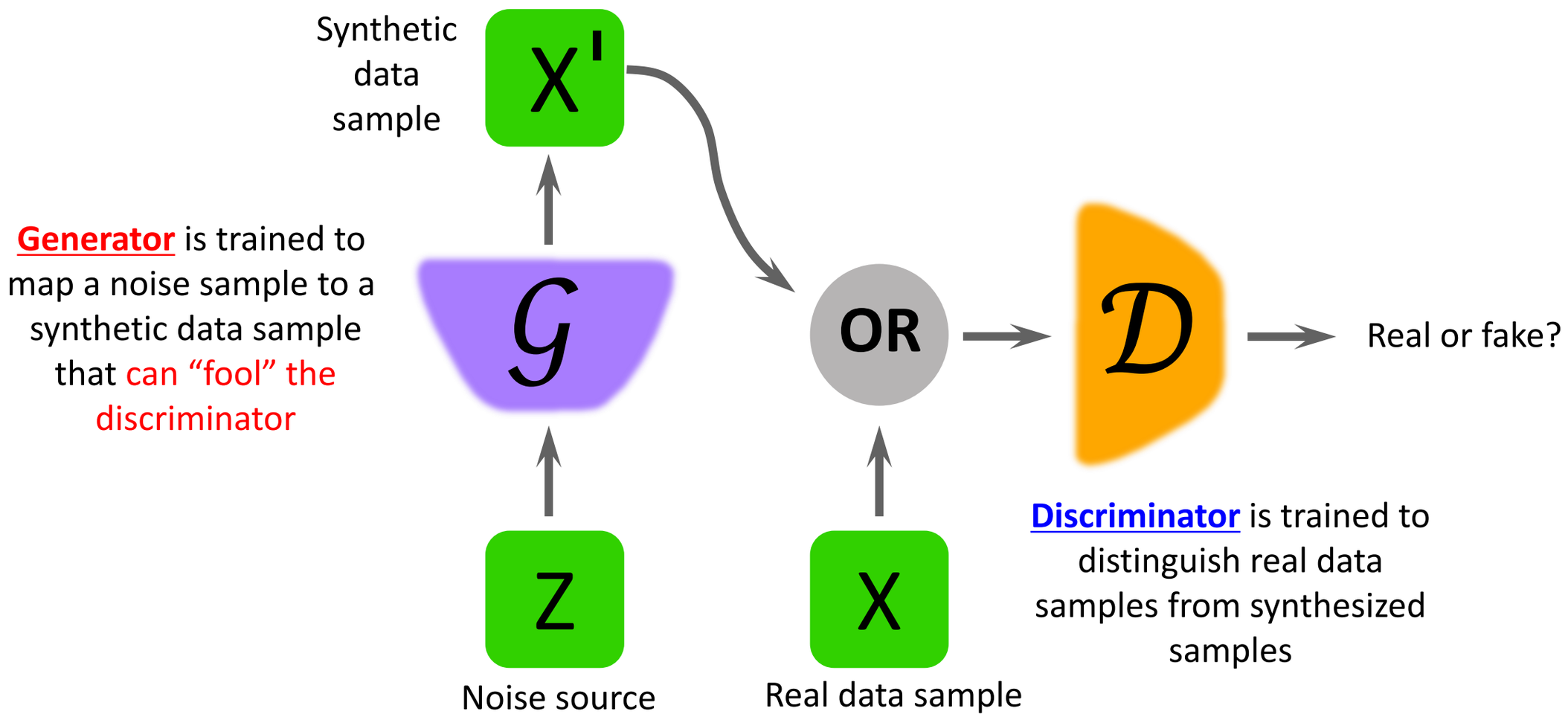
Overview of GAN (4/5)



- Discriminator network, $\mathcal{D}$, is characterized as a function that maps from image data to a probability that the image is from the real data distribution, rather than the generator distribution

- $\mathcal{D}: \mathcal{D}(\mathrm{x}) \rightarrow (0,1)$

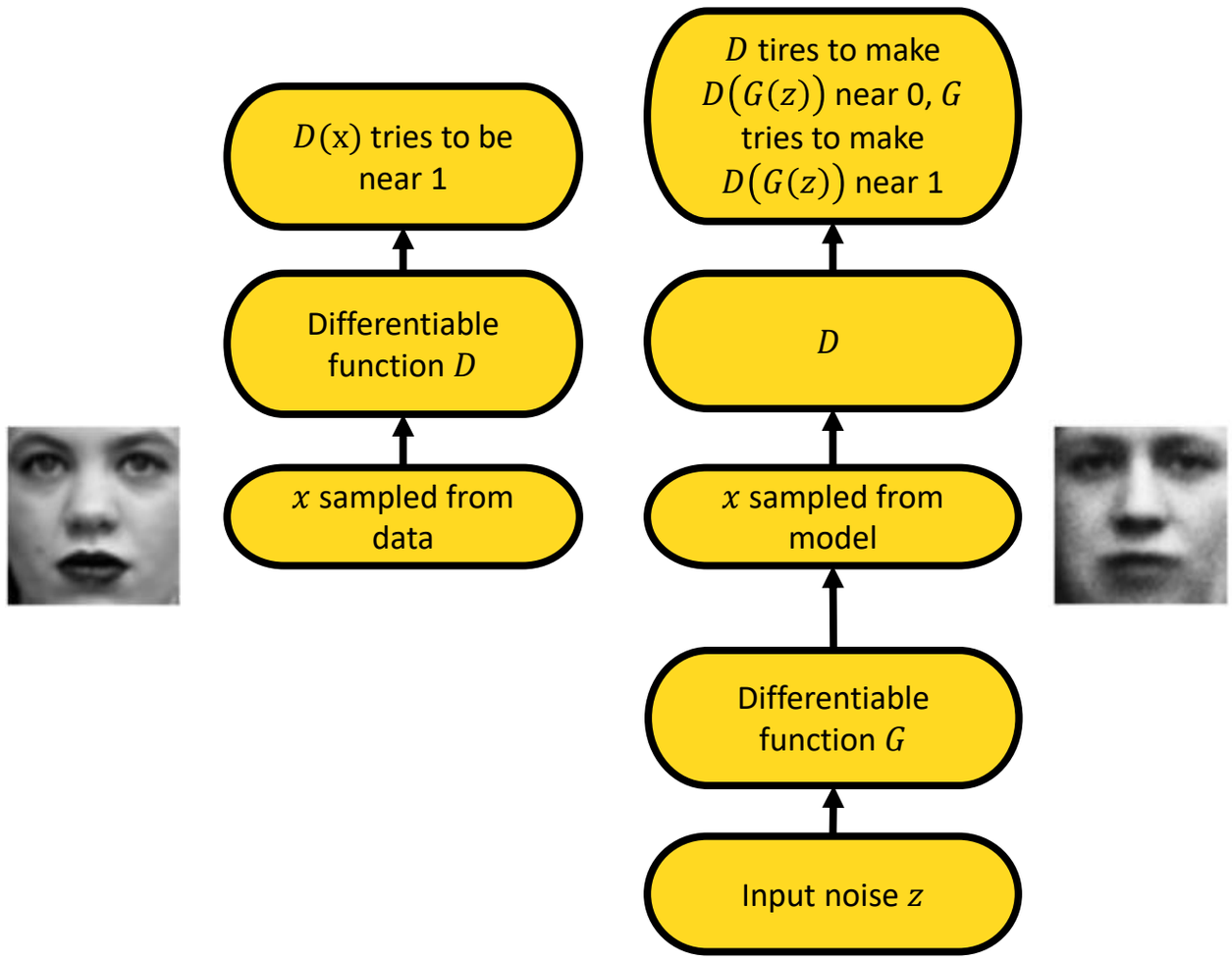
Overview of GAN (5/5)



- For a fixed generator, $\mathcal{G}$, the discriminator, $\mathcal{D}$, is trained to classify images as either being from the training data (real, close to 1) or from a fixed generator (fake, close to 0)
- If generator distribution is able to match real data distribution perfectly then the discriminator will be maximally confused, predicting 0.5 for all inputs

GAN Framework (1/2)

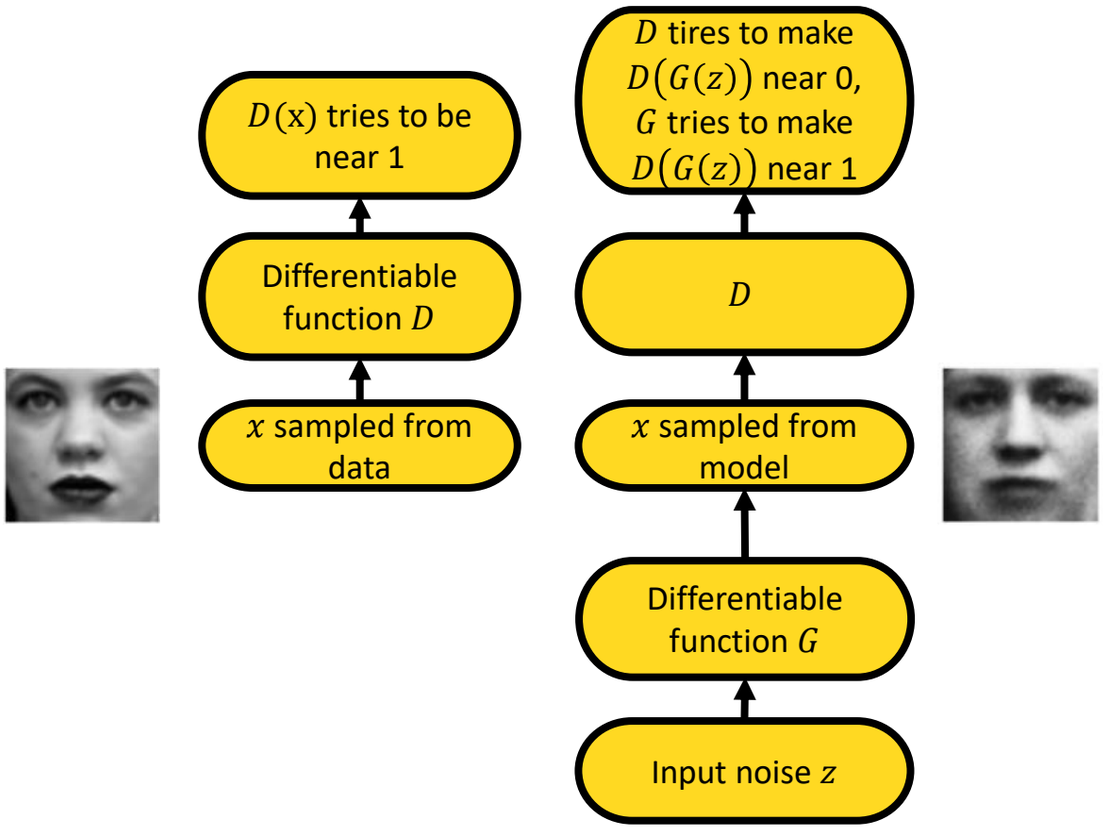
$$V(\mathcal{G},\mathcal{D}) = \mathbb{E}_{p_{data}(\mathrm{x})} \log \mathcal{D}(\mathrm{x}) + \mathbb{E}_{p_g(\mathrm{x})} \log\big(1 - \mathcal{D}(x)\big)$$



- The GAN framework pits two adversaries against each other in a game
- Each player is represented by a differentiable function controlled by a set of parameters
- The goal of discriminator(D) is to output the probability that its input is real rather than fake

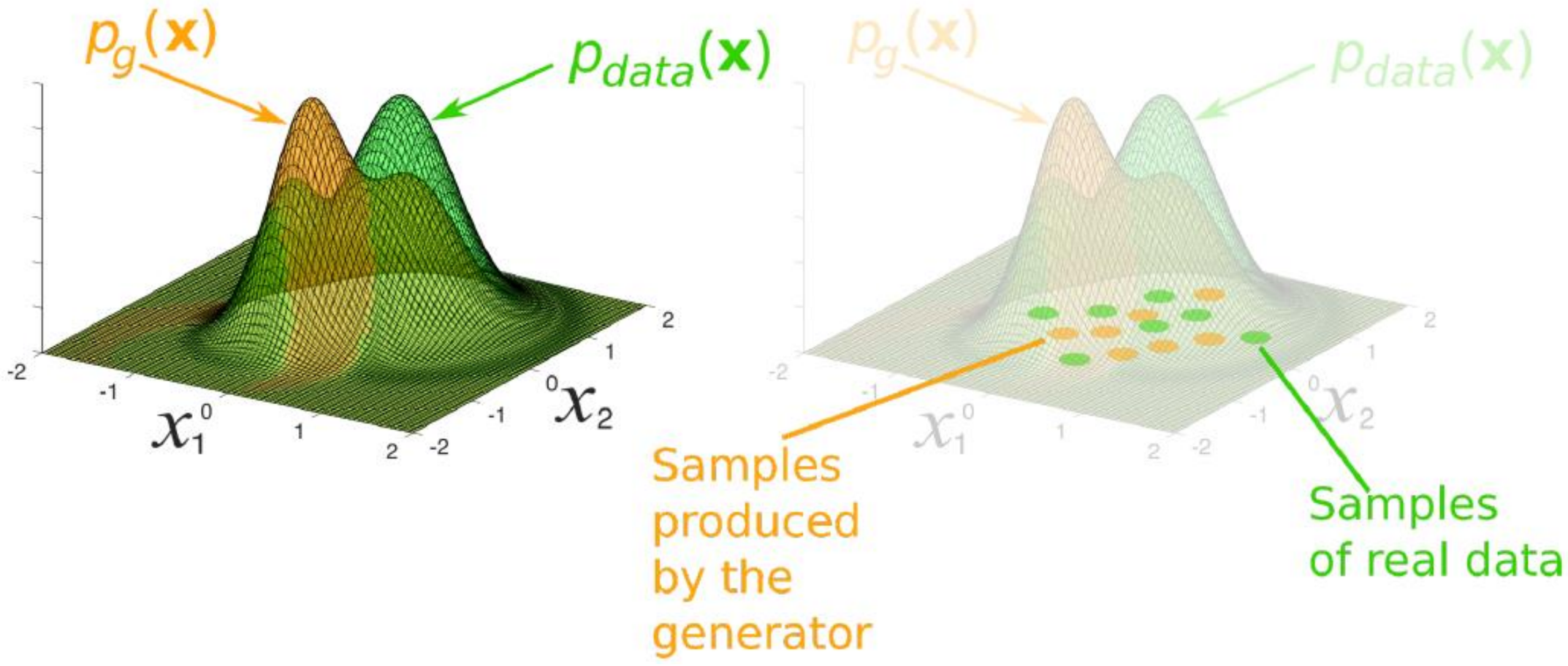
GAN Framework (2/2)

$$V(\mathcal{G},\mathcal{D}) = \mathbb{E}_{p_{data}(\mathrm{x})} \log \mathcal{D}(\mathrm{x}) + \mathbb{E}_{p_g(\mathrm{x})} \log\big(1 - \mathcal{D}(x)\big)$$



- The goal of the discriminator is for $D(x)$ to be near 1 while inputs z to the generator are randomly sampled from the model's prior over the latent variables
- The discriminator then receives input $G(z)$, a fake sample created by the generator
- The discriminator strives to make $D\big(G(z)\big)$ approach 0 while the generative strives to make the same quantity approach 1
- If both models have sufficient capacity, then the Nash equilibrium of this game corresponds to the $G(z)$ being drawn from the same distribution as the training data, and $D(x) = \frac{1}{2}$ for all x

Nash equilibrium: Capturing Data Distribution



- During GAN training, the generator is encouraged to produce a distribution of samples, $p_g(\mathrm{x})$ to match that of real data, $p_{data}(\mathrm{x})$

- For an appropriately parametrized and trained GAN, these distributions will be nearly identical

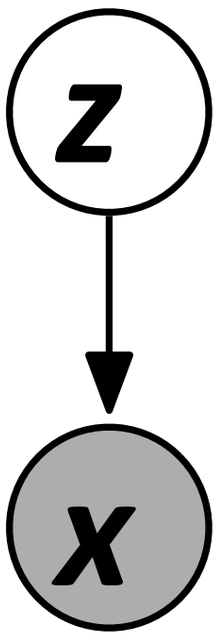
Training GANs

- Training of GANs involves both **finding the parameters of a discriminator** that maximize its classification accuracy

- At the same time, finding **the parameters of a generator which maximally confuse the discriminator**

Training GANs

❖ Generator Network



$$\boldsymbol{x} = G(\boldsymbol{z}; \boldsymbol{\theta}^{(G)})$$

- Must be differentiable
- No invertibility requirement
- Trainable for any size of *z*
- Can make *x* conditionally Gaussian given *z* but need not do so

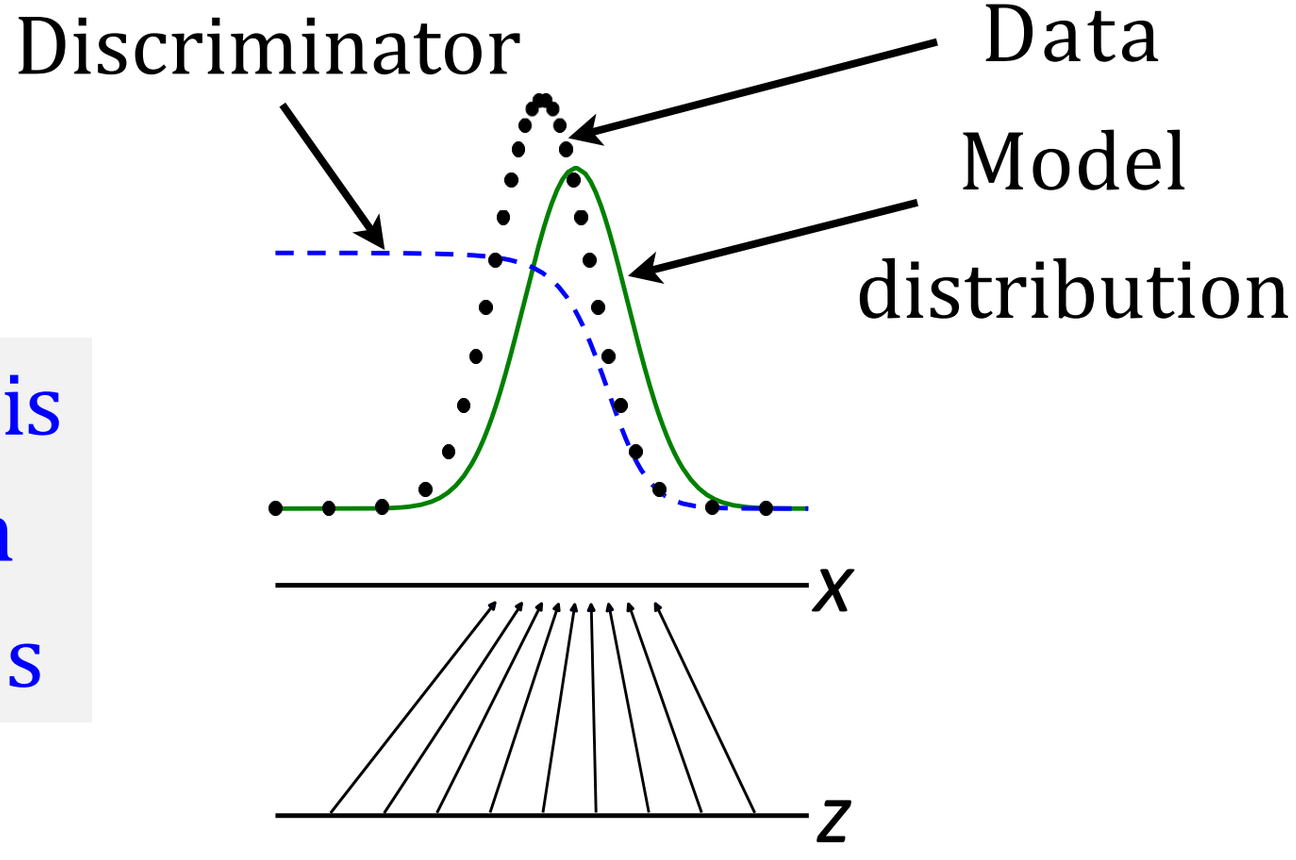
Training GANs

❖ Discriminator Strategy

Optimal $D(\boldsymbol{x})$ for any $p_{\text{data}}(\boldsymbol{x})$ and $p_{\text{model}}(\boldsymbol{x})$ is always

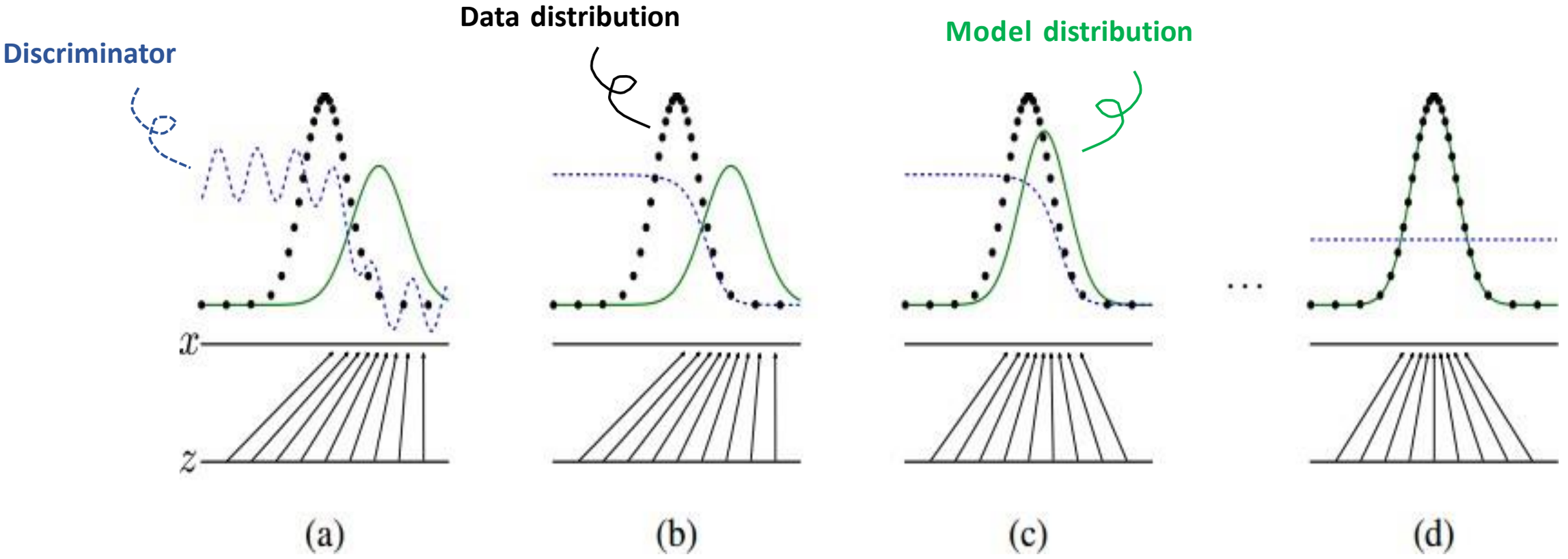
$$D(x) = \frac{p_{\text{data}}(x)}{p_{\text{data}}(x) + p_{\text{model}}(x)}$$

Estimating this ratio is the key approximation mechanism used by GANs



Training GANs

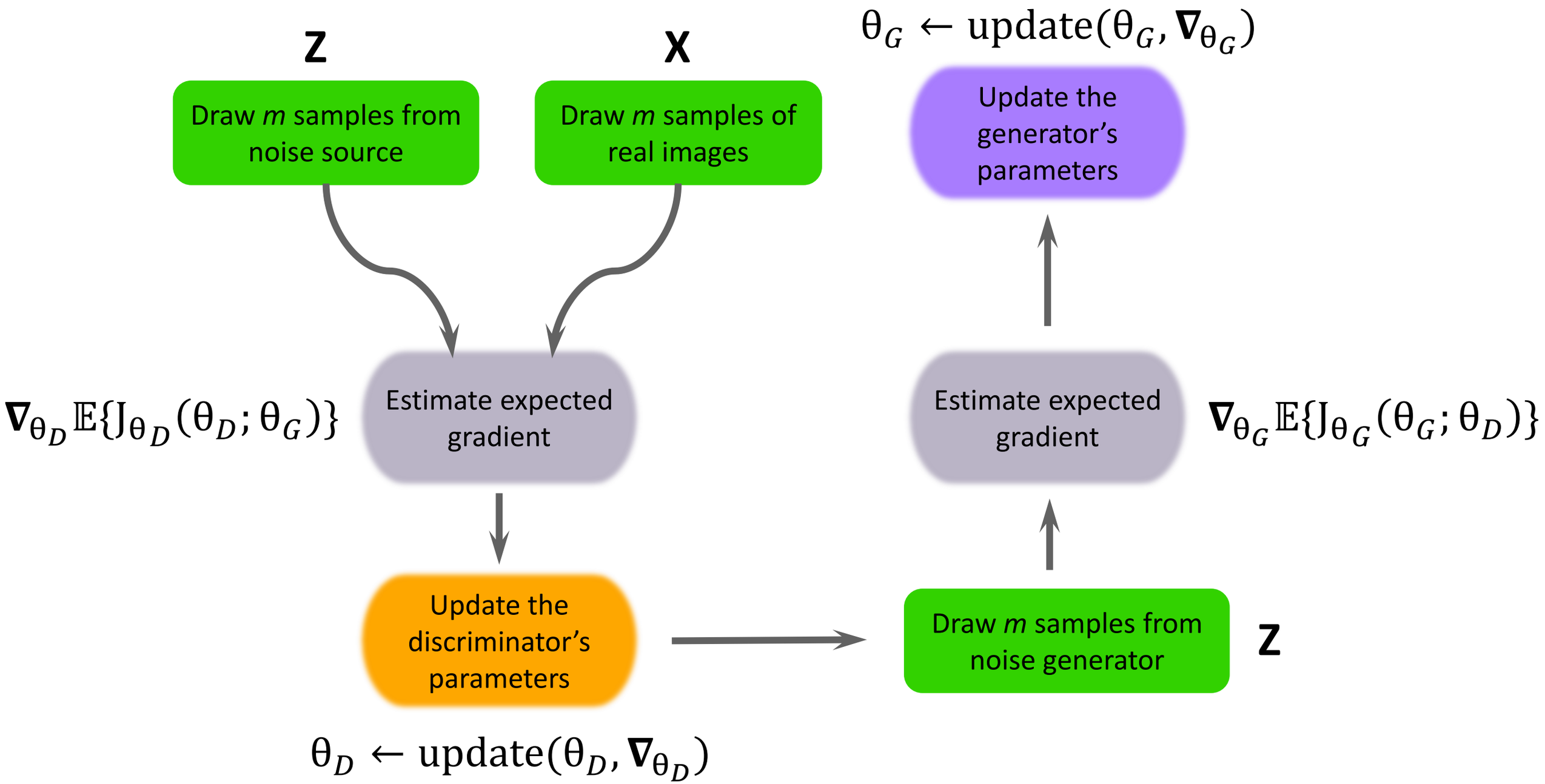
❖ Discriminator Strategy (*Cont'd*)



- GANs are trained by simultaneously updating **discriminative distribution** (*D*, blue, dashed line) so that it discriminates between samples from the data generating distribution (black, dotted line) from those of **generative (model) distribution** (green, solid line).
- The lower horizontal line is the domain from which latent variable z is uniformly sampled
- The horizontal line above is part of the domain of sample x

Training GANs

- Main loop of GAN Training



- Novel data samples, **x**', is drawn by passing random samples, **z**
- The gradient of the discriminator is updated before updating the generator

Training GANs

❖ Cost Function

$$\max_{\mathcal{D}} \min_{\mathcal{G}} V(\mathcal{G}, \mathcal{D})$$

$$V(\mathcal{G}, \mathcal{D}) = \mathbb{E}_{p_{data}(\mathrm{x})} \log \mathcal{D}(\mathrm{x}) + \mathbb{E}_{p_g(\mathrm{x})} \log\big(1 - \mathcal{D}(\mathrm{x})\big)$$

- During training, the parameters of one model are updated, while the parameters of the other are fixed
- For a fixed generator there is a unique optimal discriminator,

$$\mathcal{D}^*(\mathrm{x}) = \frac{p_{data}(\mathrm{x})}{p_{data}(\mathrm{x}) + p_g(\mathrm{x})}$$

- Generator, $\mathcal{G}$, is optimal when $p_g(\mathrm{x}) = p_{data}(\mathrm{x})$, which is equivalent to the optimal discriminator predicting 0.5 for all samples drawn from x
- In other words, the generator is optimal when discriminator, $\mathcal{D}$, is maximally confused and cannot distinguish real samples from fake ones

Training GANs

❖ Heuristic, non-saturating game

➢ Motivation

- The cost used for generator in the minimax game is useful for theoretical analysis, but does not perform especially well in practice
- When discriminator successfully rejects generator samples with high confidence, the generator's gradient vanishes
- Generator can still learn even when discriminator successfully rejects all generator samples

➢ Cost for non-saturating game

$$J^{(D)} = -\frac{1}{2}\mathbb{E}_{x\sim p_{data}} \log D(x) - \frac{1}{2}\mathbb{E}_z \log\Big(1 - D\big(G(z)\big)\Big)$$

$$J^{(G)} = -\frac{1}{2}\mathbb{E}_z \log D\big(G(z)\big)$$

Encouraging "Generator" to minimize this cost

Training GANs

❖ Training GAN describes a game rather than optimization problem

- Both players have cost functions that are defined in terms of both player's parameters
- Discriminator wishes to minimize $J^{(D)}\left(\theta^{(D)}, \theta^{(G)}\right)$ and must do so while controlling only $\theta^{(D)}$
- Generator wishes to minimize $J^{(G)}\left(\theta^{(D)}, \theta^{(G)}\right)$ and must do so while controlling only $\theta^{(G)}$

Because each player's cost depends on the other player's parameters, but each player cannot control the other player's parameters, this scenario is most straightforward to describe as a **game rather than as an optimization problem**

Training GANs

❖ The solution to a game is Nash equilibrium

- The solution to an **optimization problem** is a (local) minimum, a point in parameter space where all neighboring points have greater or equal cost

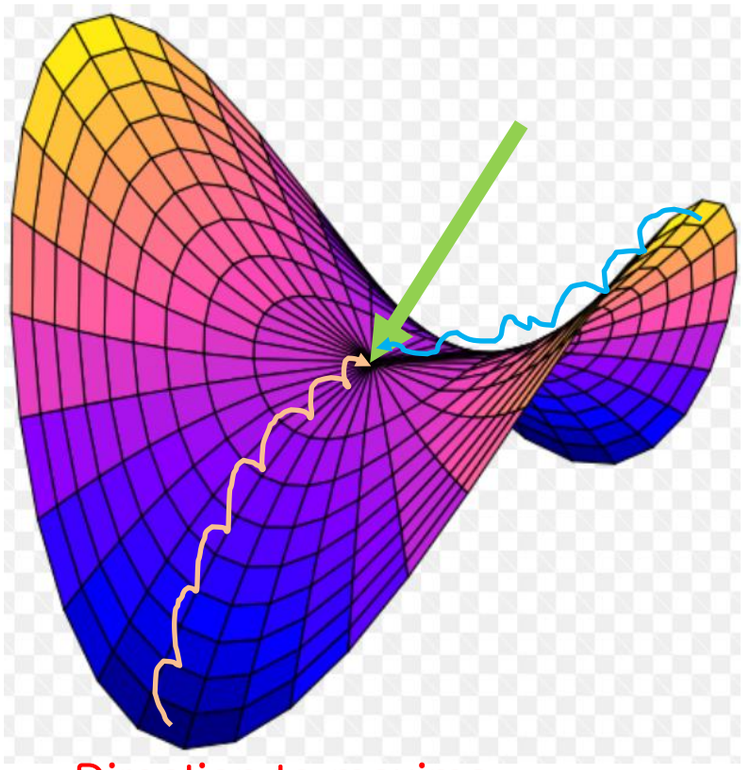
- **The solution to a game is a Nash equilibrium**

- Nash equilibrium is a tuple $(\theta^{(D)}, \theta^{(G)})$ that is a local minimum of $J^{(D)}$ with respect to $\theta^{(D)}$ and a local minimum of $J^{(G)}$ with respect to $\theta^{(G)}$

Research Issues

❖ Non-convergence

- GANs require finding **the equilibrium to a game** with two players
- Optimization algorithms often approach a **saddle point** or local minimum rather than a global minimum



Research Issues

❖ Non-convergence (*Cont'd*)

- For some games, simultaneous gradient descent does converge, and for others, it does not
- For GANs, there is no theoretical prediction as to whether simultaneous gradient descent should converge or not
- Developing algorithms guaranteed to converge remain important open research problem

Research Issues

❖ Non-convergence (*Cont'd*)

- For some games, simultaneous gradient descent does converge, and for others, it does not
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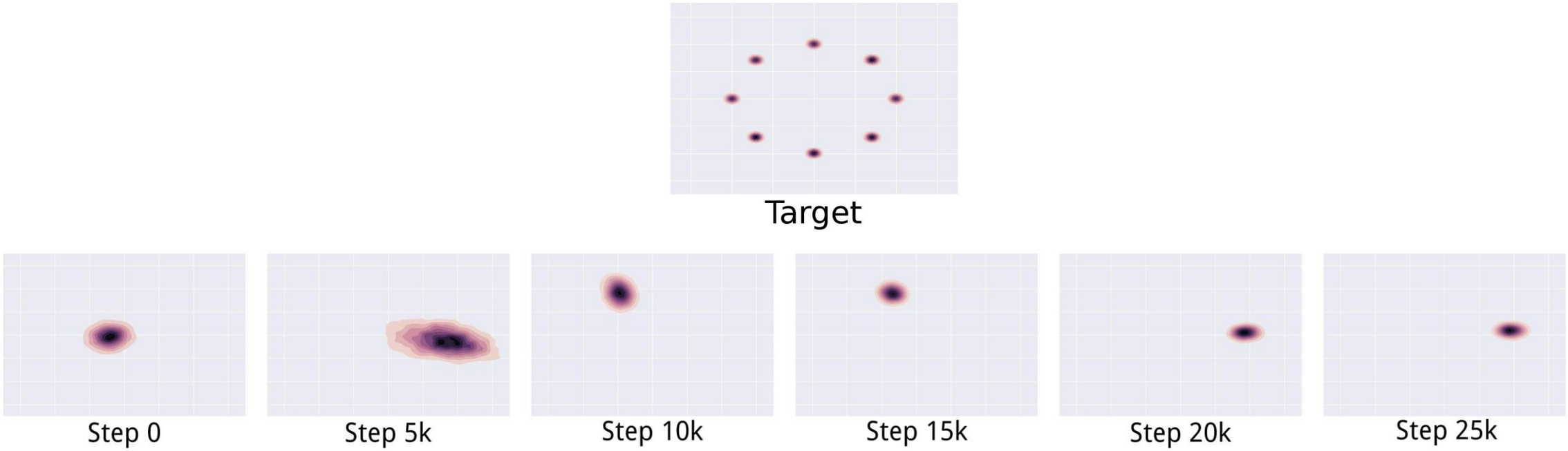
Research Issues

❖ Mode Collapse

- Problem that occurs when the generator learns to map several different input **z** values to the same output point
- **Partial mode collapse** : Generator makes multiple images that contain the same color or texture themes, or multiple images containing different views of the same object

Research Issues

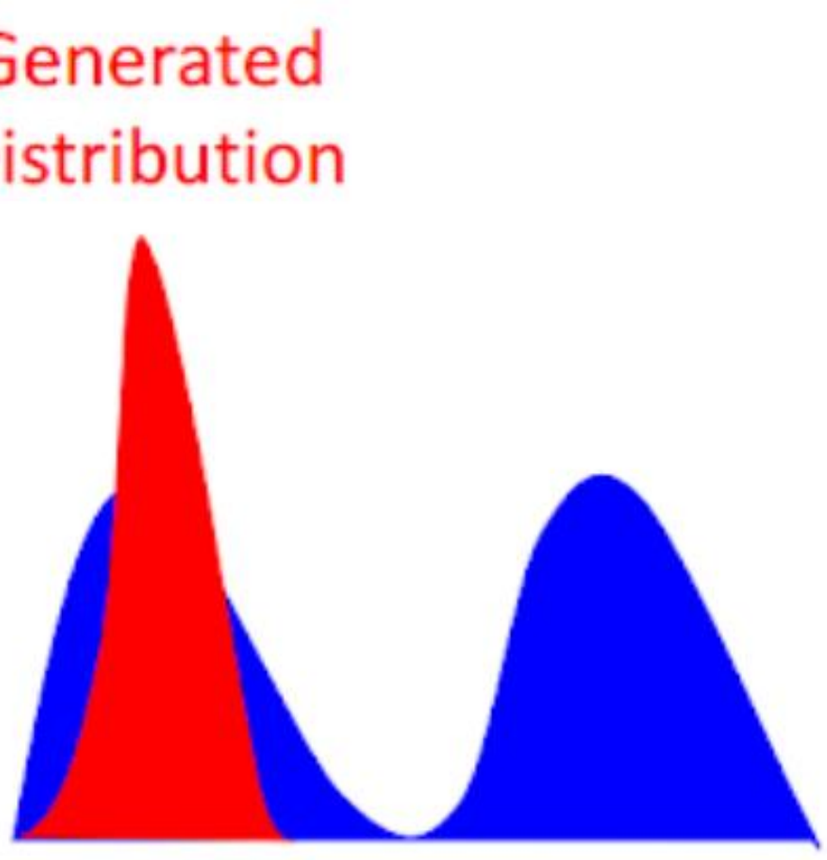
❖ Mode Collapse (*Cont'd*)



Rather than converging to a distribution containing all of the modes in the training set, generator only ever produces a single mode at a time, cycling between different modes as the discriminator learns to reject each one

Research Issues

❖ Mode Collapse (*Cont'd*)



Conclusion

- GANs are generative models that use supervised learning to approximate an intractable cost function
- GANs can simulatemany cost functions, including the one used for maximum likelihood
- Finding Nash equilibria in high-dimensional, continuous, non-convex games is an important open research problem
- GANs are a key ingredient of PPGNs, which are able to generate compelling high resolution samples from diverse image classes