CS-4053 Recommender System

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Lecture 10: Generative Adversarial Network (GAN)

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Introduction

❑ **Generative Adversarial Networks** *(GANs)* is an unsupervised architecture that use two neural networks, competing against each other (thus the "*adversarial*") in order to generate new, synthetic instances of data that can pass for real data.

❑ GANs can learn to *mimic* any distribution of data.

❑ It can be used for image generation, voice generation and video generation tasks.
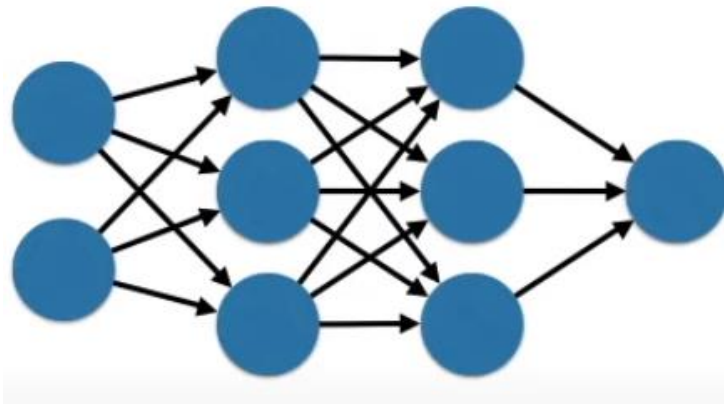
Image Generation

❑ [This Person Does Not Exist - Random Face Generator (this-person-does-not-exist.com)](this-person-does-not-exist.com)
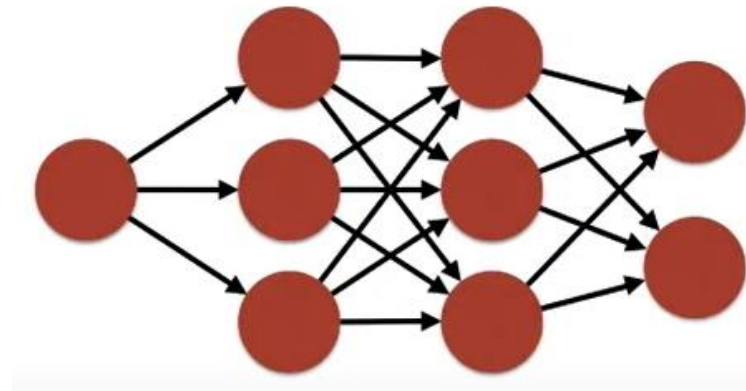
Introduction

❑ A simple GAN architecture consists of two networks, a **generator** and a **discriminator**.

Generator

Discriminator

Introduction

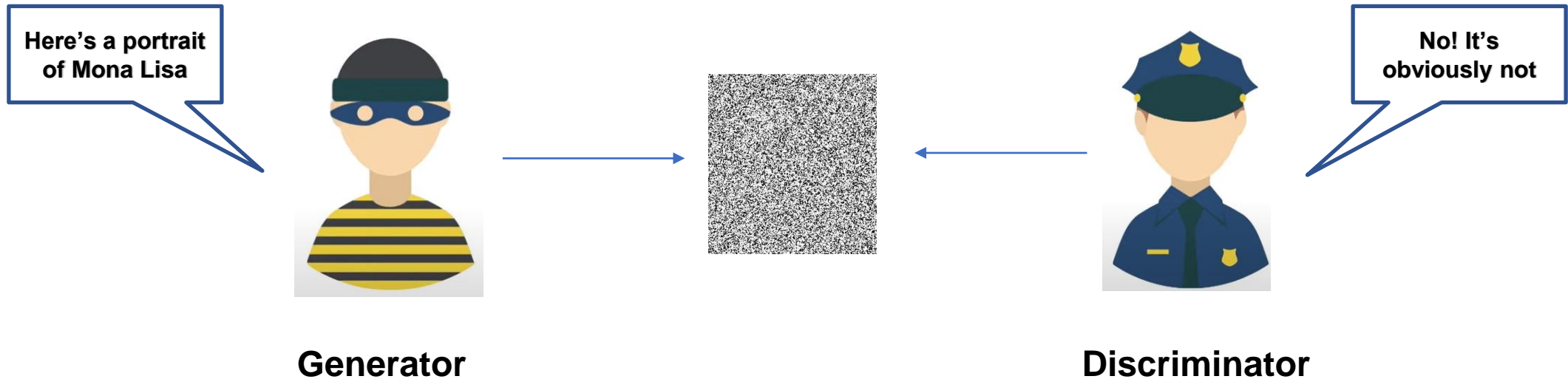❑ A simple GAN architecture consists of two networks, a **generator** and a **discriminator**.
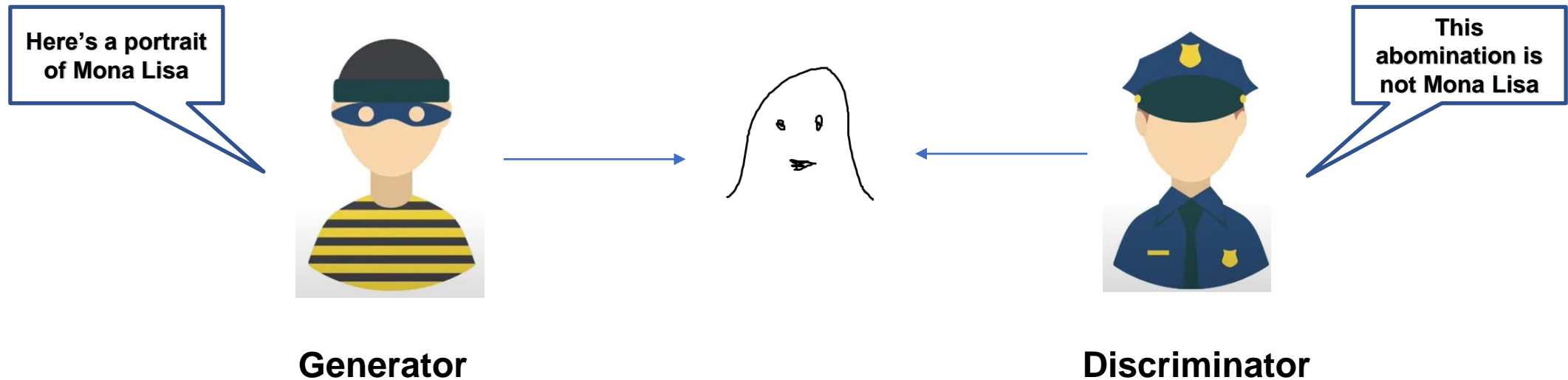
Generator

Discriminator

Adversarial Learning

❑ The **generator** starts with random noise and tries to mimic the target distribution *(e.g., image of a digit, image of Mona Lisa)*.

Here's a portrait of Mona Lisa

No! It's obviously not

Generator

Discriminator

Adversarial Learning

❑ The **discriminator** has already seen the training data thus it knows what the target distribution is like thus it acts as a critic.
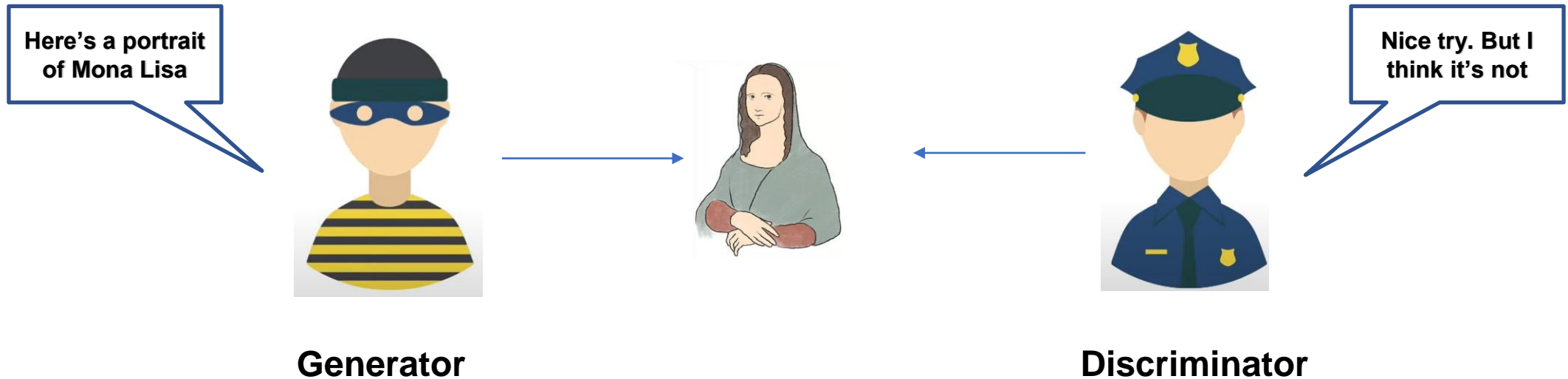
Generator

Discriminator

Adversarial Learning

❑ The **generator** repeatedly tries to fool the discriminator into believing that the generated distribution (image) is a real one.
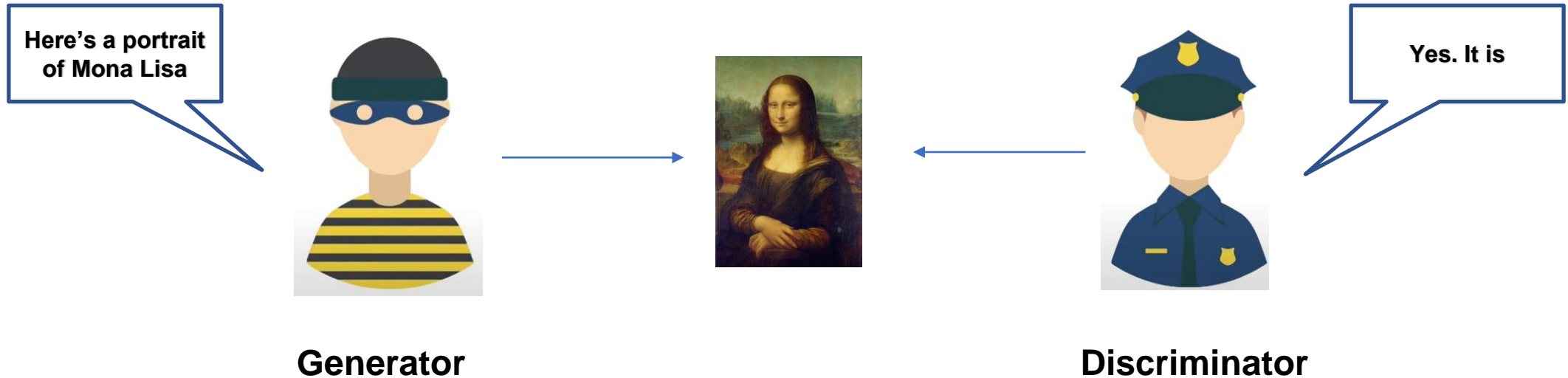

Generator
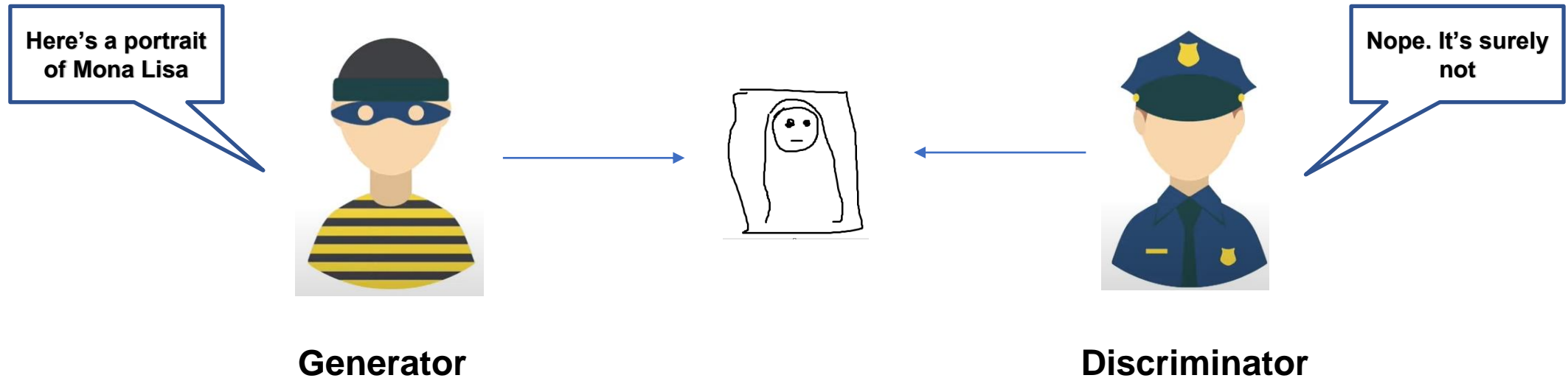
Discriminator

Adversarial Learning

❑ Based on the feedback *(loss)* of the **discriminator** the quality of generated output is gradually improved.

Generator

Discriminator

Adversarial Learning

❑ This adversarial learning is a two-player game between the **generator** and the **discriminator**.

Generator

Discriminator
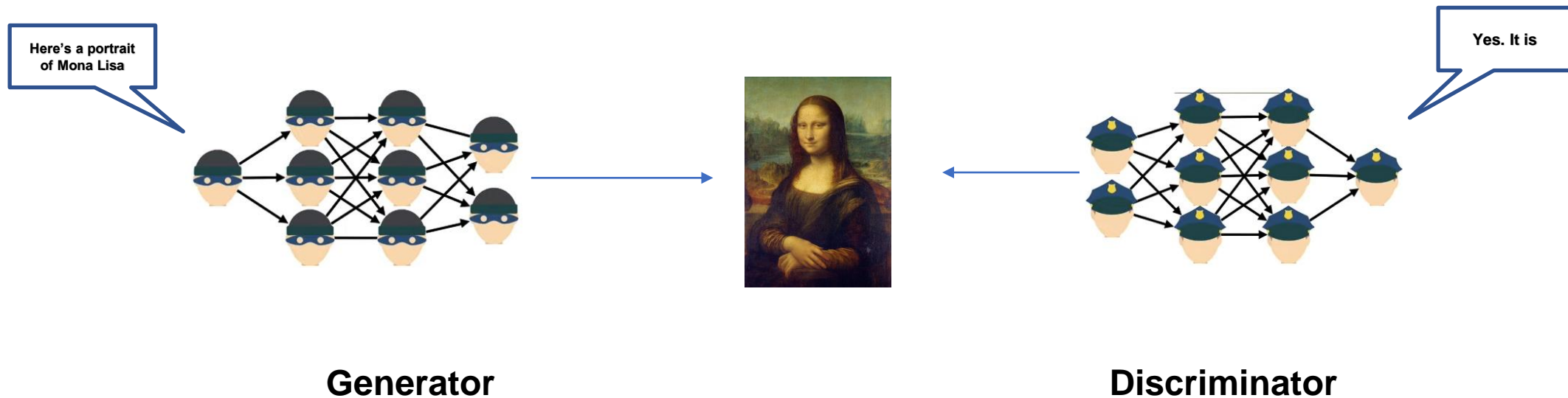
Adversarial Learning

❑ This adversarial learning is a two-player game between the **generator** and the **discriminator**.
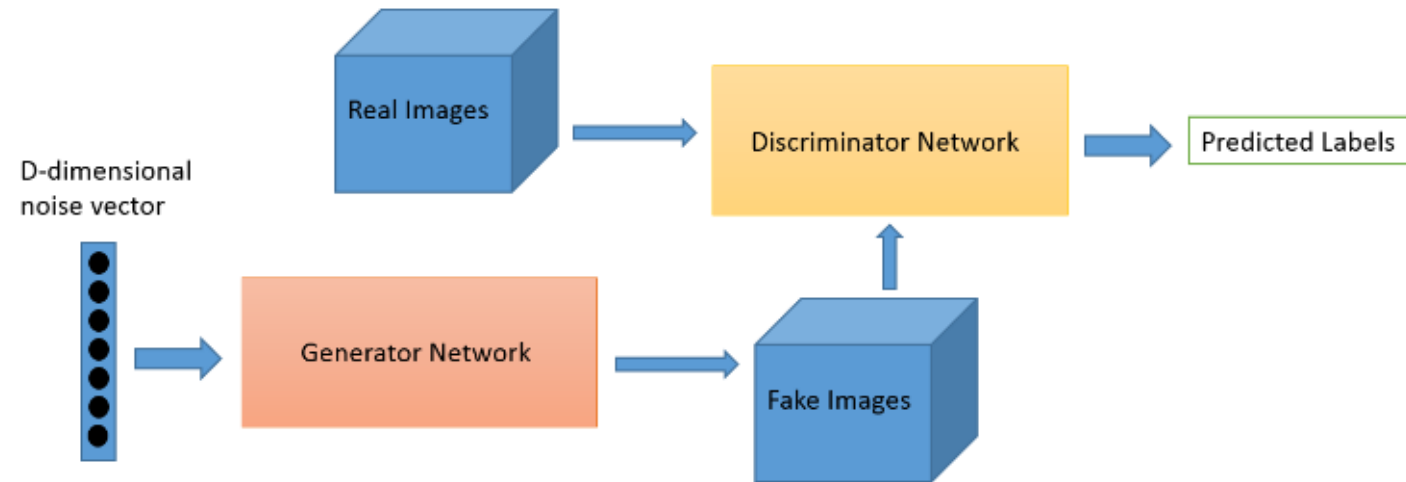

Generator

Discriminator

Steps taken by GAN:

– *The generator takes in random numbers and returns an image.*

– *This generated image is fed into the discriminator alongside a stream of images taken from the actual, ground-truth dataset.*

– *The discriminator takes in both real and fake images and returns probabilities, a number between 0 and 1, with 1 representing a prediction of authenticity and 0 representing fake.*

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

$$V(D, G) = \mathbb{E}_{x \sim p_{data}(x)}[\log D(x)] + \mathbb{E}_{z \sim p_z(z)}[\log(1 - D(G(z)))]$$

Steps taken by GAN:

Image Credits: O'Reilly

Example: Generating MNIST digits

❏ For MNIST, the discriminator network is a standard convolutional network that can categorize the images fed to it, a binomial classifier labeling images as real or fake.

❏ The generator is an inverse convolutional network that takes a vector of random noise and upsamples it to an image

Example: Generating MNIST digits
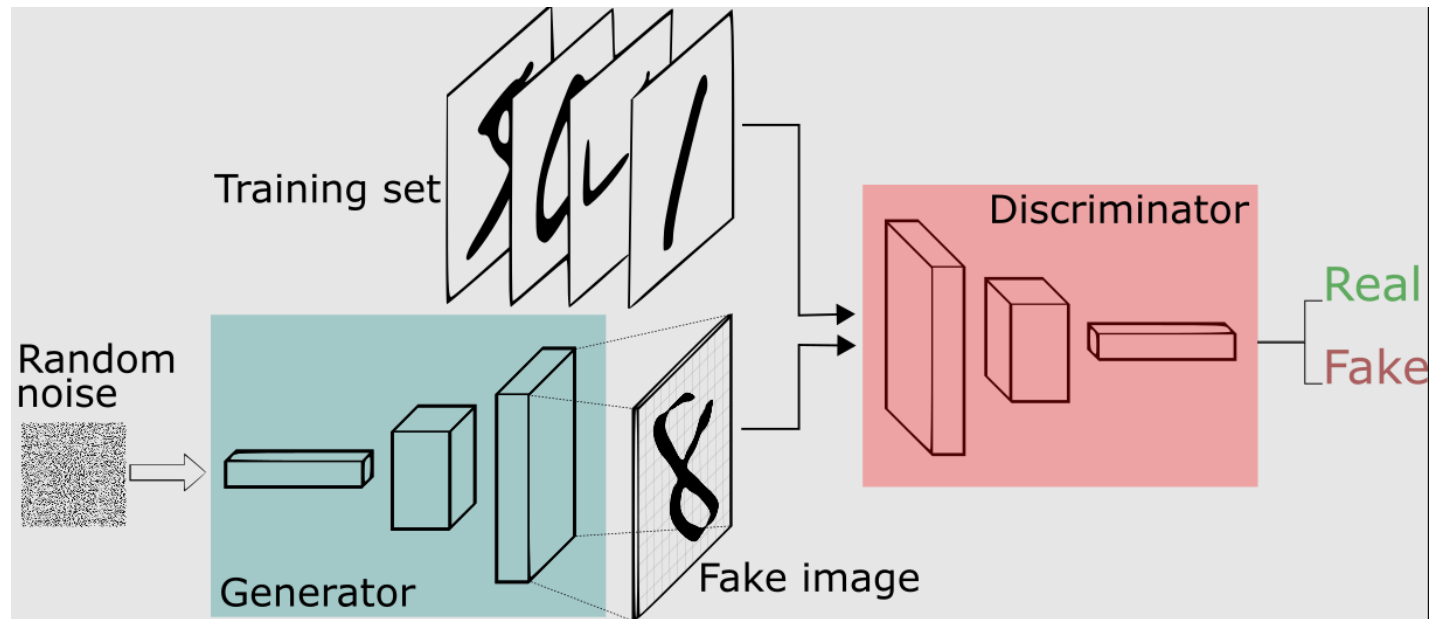
How to train a GAN

❑ Build your generator and discriminator models

❑ Sample data from true distribution and train discriminator on this data

   ❑ Discriminator works as a binary classifier

❑ Create input data from latent space (noise) and feed it to the generator

❑ The generator output serves as input to the discriminator

❑ The discriminator uses Sigmoid activation to classify the generated output as real or fake

❑ The discriminator loss is fed-back to the generator

❑ The generator is trained until it reaches convergence

Challenges

❑ GANs are really hard to train!

❑ Hard to meet convergence criteria.

❑ Vanilla GANs suffer from vanishing gradient problem.

❑ Overwhelming adversary i.e. one network should not "*overpower*" another

❑ Cannot count objects *(Stable Diffusion can help)*

❑ Sensitive to choice of hyperparameters

❑ *...and many other challenges*

Guidelines for training

❑ Use tanh activation for generator and sigmoid for generator

❑ Freeze generator for every other training iteration of discriminator

❑ Use LeakyReLU in dense layers

❑ Use Functional API (for Keras)

❑ Use dropout

Types of GANs

- ❏ Vanilla GANs (original model)
- ❏ CGAN
- ❏ Wasserstein GAN
- ❏ StyleGAN
- ❏ InfoGAN
- ❏ DCGAN
- ❏ DualGAN
- ❏ KDGAN
- ❏ *... many other variants*

Which architecture to use for RecSys?

- Vanilla GANs (original model)
- **CGAN**
- Wasserstein GAN
- **StyleGAN**
- InfoGAN
- DCGAN
- DualGAN
- KDGAN
- *... many other variants*