California State University
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Machine Learning

Generative Adversarial Networks (GANs)

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Agenda Overview

01 What is GANs

02 GAN Architecture

03 Generator Model

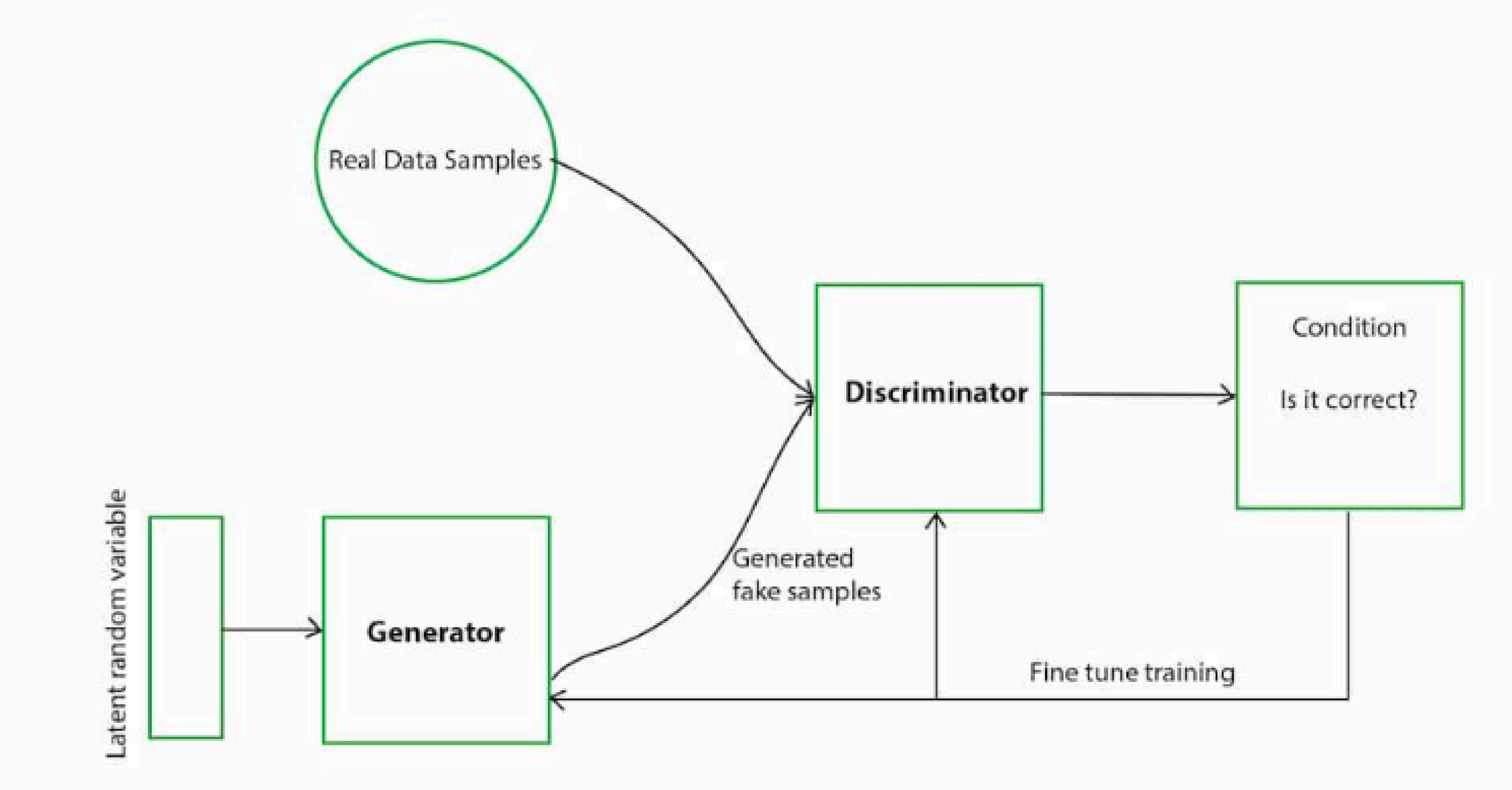
04 Discriminator Model

05 How GANs Works

Generative Adversarial Networks (GANs)

- Proposed by: Ian Goodfellow et al., 2014
- Core Idea: Two networks compete in a zero-sum game
  - Generator (G): Tries to create realistic data
  - Discriminator (D): Tries to distinguish real from fake
- Adversarial Training: The networks improve through competition

GAN Architecture



1. Generator Model

- The generator is a deep neural network.
- It takes random noise (usually from a Gaussian or uniform distribution) as input.
- Its goal is to generate realistic data samples (e.g., images, text, etc.).
- It learns to mimic the underlying data distribution.
- Training happens via backpropagation, using gradients from the discriminator's feedback.
- The generator's objective is to fool the discriminator into classifying fake samples as real.
- Over time, it improves by producing samples that are increasingly indistinguishable from real data.

Generator Loss Function: The generator tries to minimize this loss:

$$J_G = -\frac{1}{m}\Sigma_{i=1}^{m} log D(G(z_i))$$

where

J_G measure how well the generator is fooling the discriminator.

$G(_{zi})$ is the generated sample from random noise zizi

$D(G(_{zi}))$ is the discriminator's estimated probability that the generated sample is real.

2. Discriminator Model

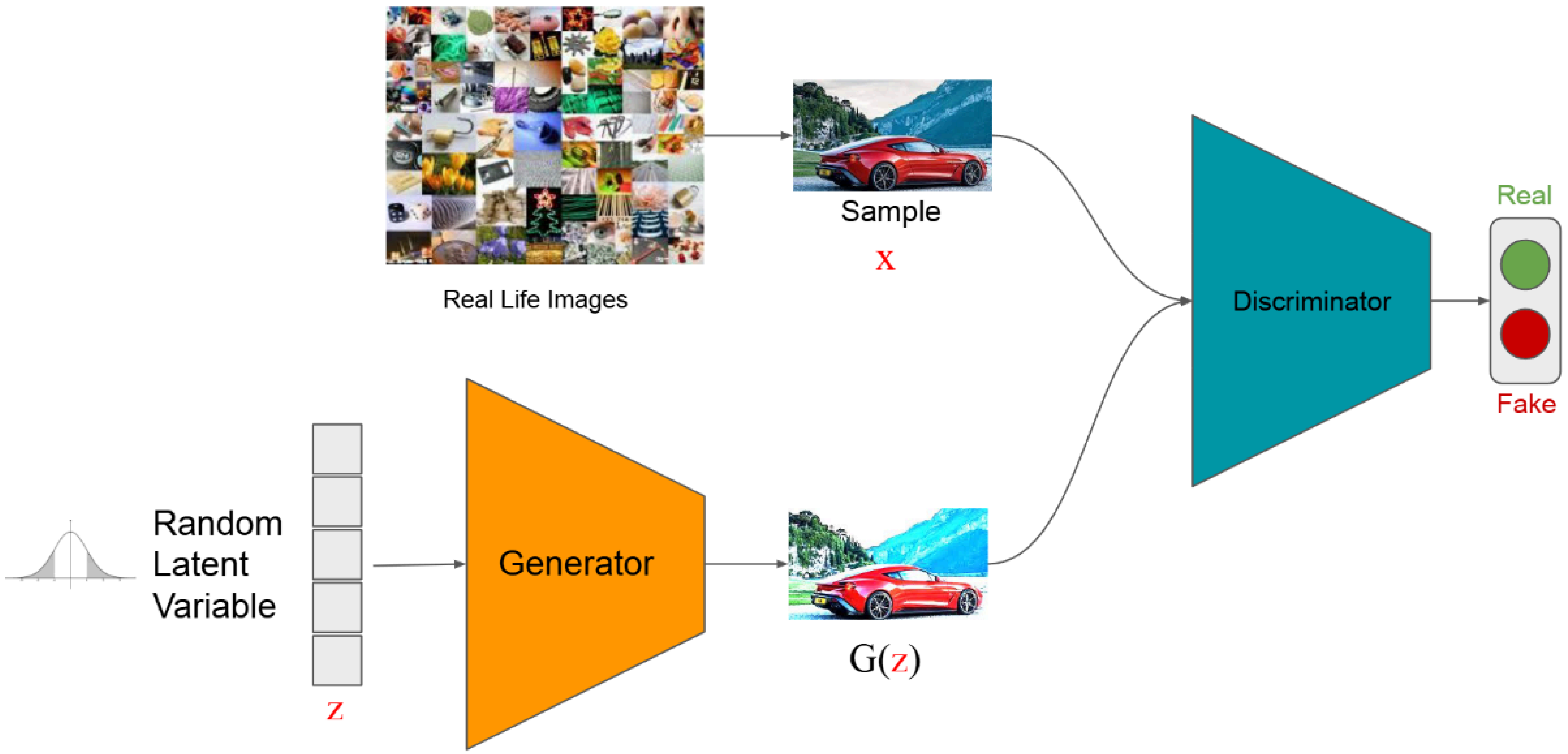
- The discriminator acts as a binary classifier, distinguishing between real and generated (fake) data.
- It learns during training by adjusting its parameters to improve its ability to detect fake samples.
- Its goal is to maximize accuracy in telling apart real from generated data, which helps improve overall model performance.
- In tasks involving image or 3D grid data, it typically uses convolutional layers to extract spatial features.
- These features help the discriminator identify subtle patterns, enhancing its ability to evaluate the realism of generated outputs.
- By challenging the generator during training, the discriminator drives the generator to produce more realistic results.

Discriminator Loss Function:

$$J_D = -\frac{1}{m}\Sigma_{i=1}^{m} log\ D(x_i) - \frac{1}{m}\Sigma_{i=1}^{m} log(1 - D(G(z_i))$$

J_D measures how well the discriminator classifies real and fake samples.
x_i is a real data sample.
$G(_{zi})$ is a fake sample from the generator.
$D(_{xi})$ is the discriminator’s probability that xixi is real.
$D(G(_{zi}))$ is the discriminator’s probability that the fake sample is real.

How GANs Work



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Thank You

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