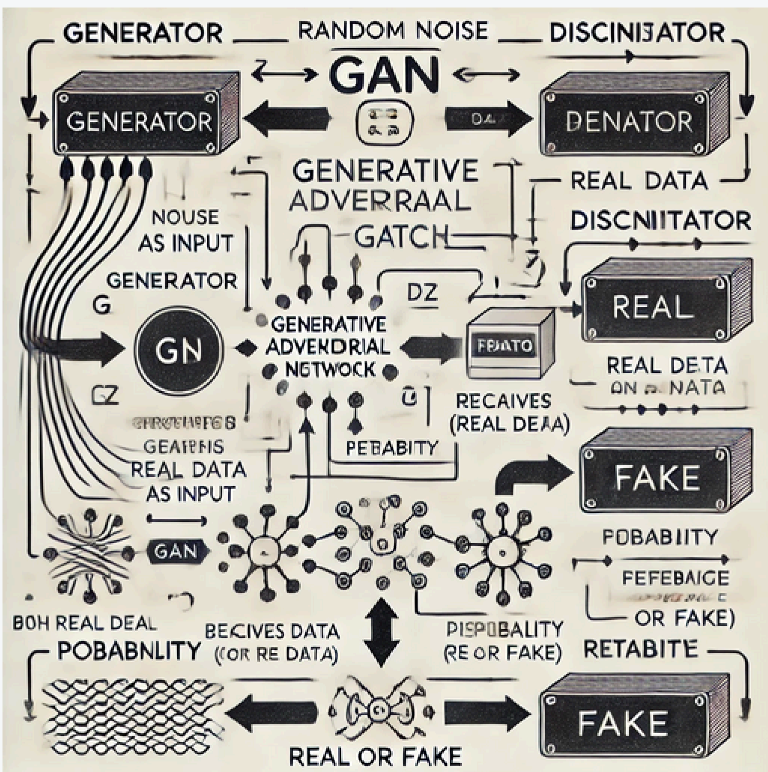
POST 33 - GEN AI

GENERATIVE AI
FOR ALL

What are

Generative Adversarial Networks (GANs)



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Definition

- Generative Adversarial Networks (GANs) are an essential advancement in deep learning, with the unique capability to generate synthetic data by pitting two neural networks—generator and discriminator—against each other in an adversarial process.

- Since their inception, GANs have been widely adopted in tasks such as image synthesis, data augmentation, and even unsupervised learning.

Key Concepts of GANs:

Generator:

- **Purpose**: Generates synthetic data (e.g., images, text) from random noise.
- **Goal**: Create data that looks as real as possible to fool the discriminator.
- Uses latent space to learn complex patterns.

Key Concepts of GANs:

Discriminator:

- **Purpose:** Distinguishes between real data and the synthetic data generated by the generator.

- **Goal:** Correctly classify the input as "real" (from the true data) or "fake" (from the generator).

Key Concepts of GANs:

Adversarial Process:

- The generator and discriminator are trained simultaneously in a zero-sum game, meaning that the success of one network is the failure of the other.

- The generator improves by learning to fool the discriminator, while the discriminator improves by distinguishing between real and fake data.

Key Concepts of GANs:

Loss Function:

- GANs use a minimax game where the generator tries to minimize the probability of the discriminator being correct, and the discriminator tries to maximize it. This can be formalized using a loss function:

$$\min_G \max_D V(D, G) =$$

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

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How GANs Work:

Step 1: Initialize the Networks

- The generator is initialized to produce random outputs.
- The discriminator is initialized to classify real and generated data.

Step 2: Training the Discriminator

- The discriminator is first trained on real data and synthetic data produced by the generator.
- The discriminator updates its weights to correctly classify real versus fake data.

How GANs Work:

Step 3: Training the Generator

- The generator is trained by adjusting its weights to produce data that fools the discriminator.
- The generator doesn't have direct access to real data; instead, it gets feedback from the discriminator's predictions.

How GANs Work:

Step 4: Iteration

- This process continues iteratively, where both networks are updated over time. The generator improves its ability to generate realistic data, and the discriminator sharpens its ability to tell real from fake.
- Ideally, this leads to a scenario where the generator produces data indistinguishable from real data.

Applications of GANs:

Image and Video Generation:

- GANs are powerful tools for creating high-quality synthetic images. Popular use cases include:
- Deepfakes: Generating highly realistic faces.
- Super-resolution: Enhancing image quality, as seen in SRGAN (Super-Resolution GAN).
- Style Transfer: Generating art from photos or combining styles, e.g., using CycleGAN for image-to-image translation.

Applications of GANs:

Data Augmentation:

- GANs help increase the variety of training data, especially in fields like medical imaging or autonomous driving where labeled data is scarce:
- Image Augmentation: GANs can produce new variations of images to diversify the training set.
- Tabular Data Augmentation: GANs, such as CTGAN (Conditional Tabular GAN), are used to augment tabular data in scenarios like fraud detection and healthcare.

Applications of GANs:

Anomaly Detection:

- GANs can be leveraged to model the distribution of normal data, detecting anomalies by recognizing deviations from the generated samples:
- Applications: Fraud detection, network intrusion detection, and industrial equipment monitoring.

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Types of GANs

Vanilla GAN:

- The basic form of GAN introduced by Ian Goodfellow. It consists of a simple generator and discriminator trained on the same data.

Conditional GAN (cGAN):

- Condition the generator on additional information, such as class labels, allowing data generation based on specific conditions (e.g., generating images of dogs with specific attributes).

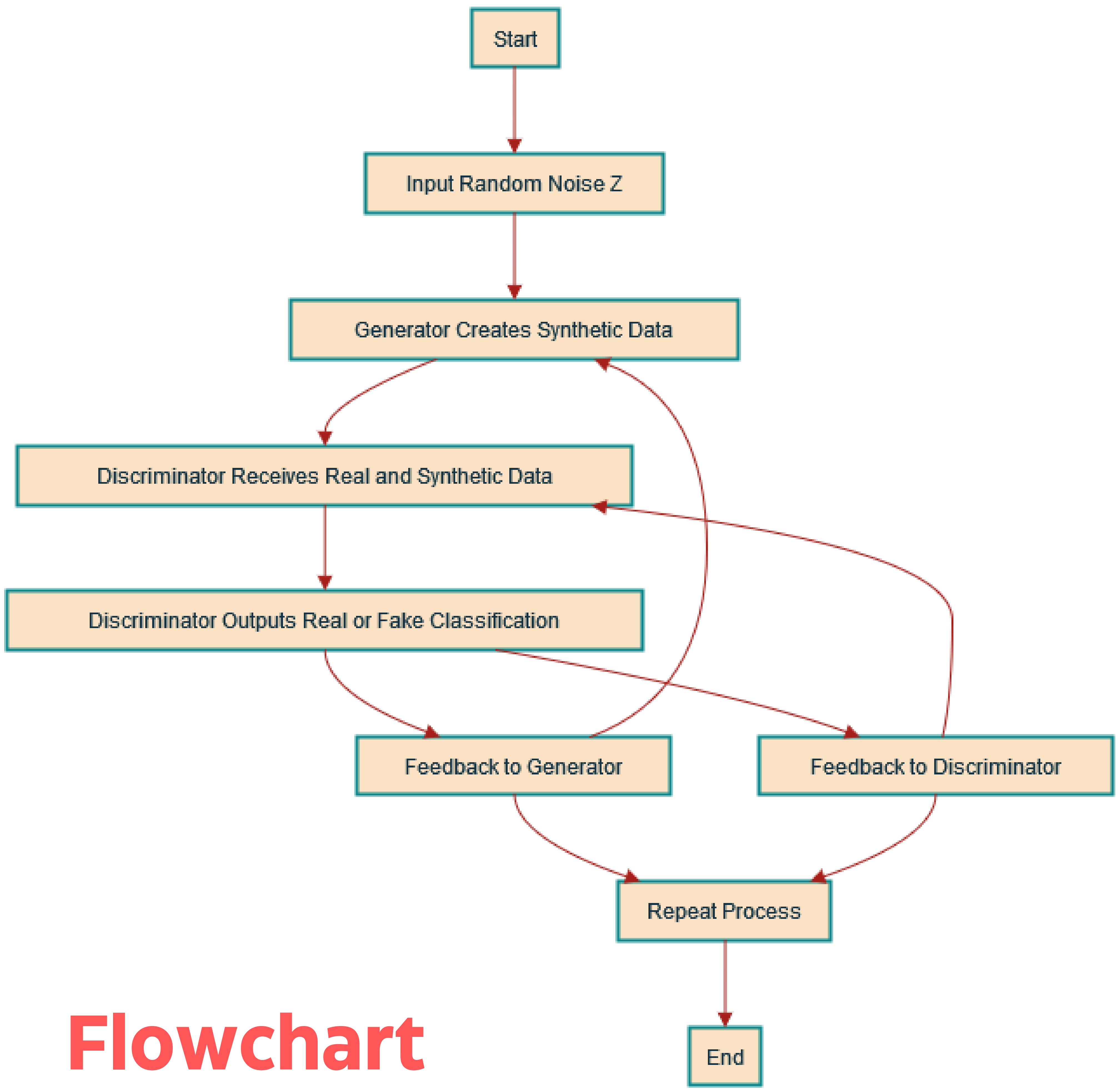
Types of GANs

Deep Convolutional GAN (DCGAN):

- DCGANs employ convolutional layers, making them particularly effective for image generation. They are widely used in image-related tasks due to their ability to capture spatial hierarchies in images.

CycleGAN:

- This GAN is used for unpaired image-to-image translation tasks, like converting photographs into paintings or vice versa without requiring paired training data.



Flowchart

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THANK YOU

- Special thanks to Gemini and Chatgpt for all the help on content
- Follow along for more informative articles in Generative AI space

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