GENERATIVE ADVERSARIAL NETWORK

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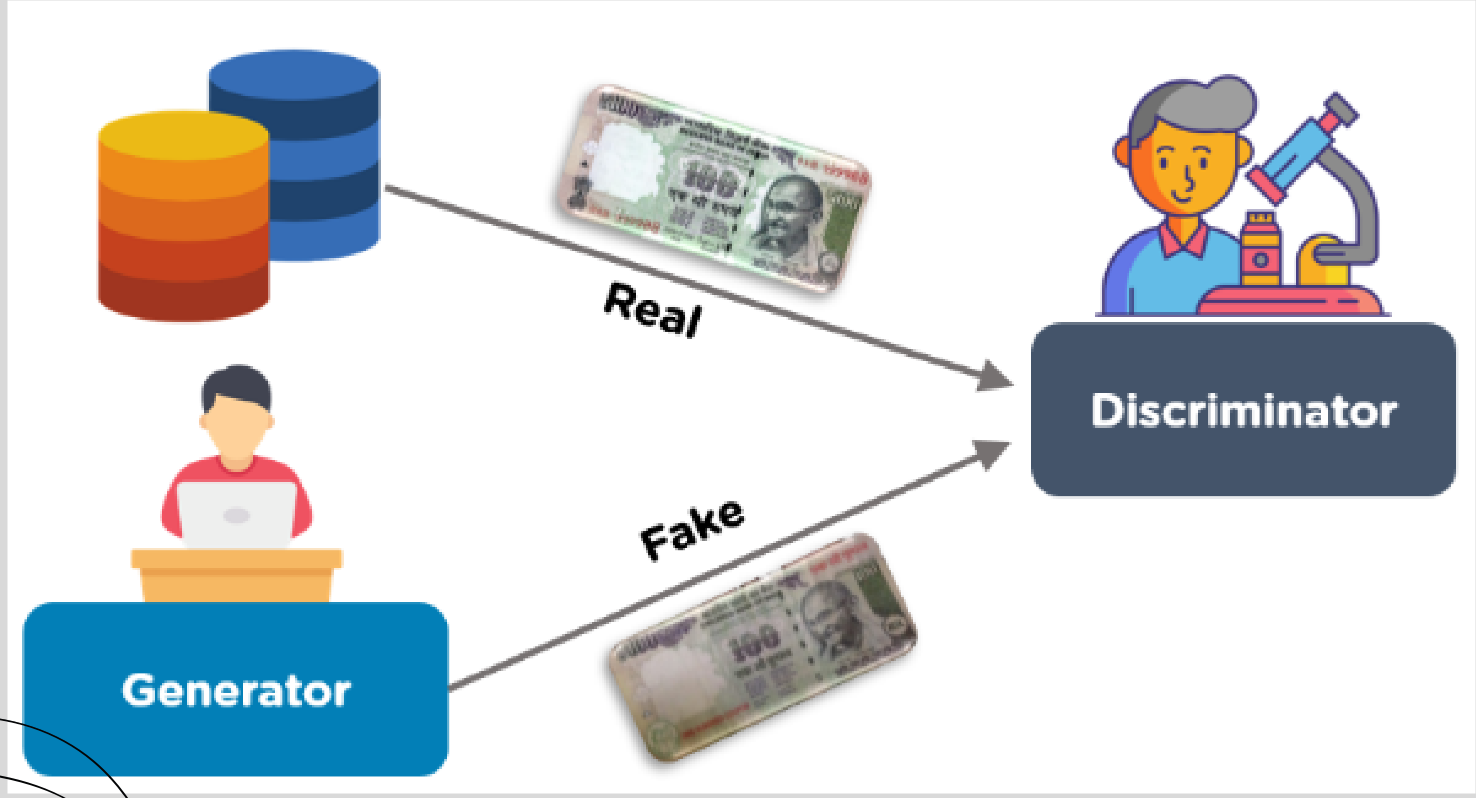
CONTENT

INTRODUCTION TO GAN

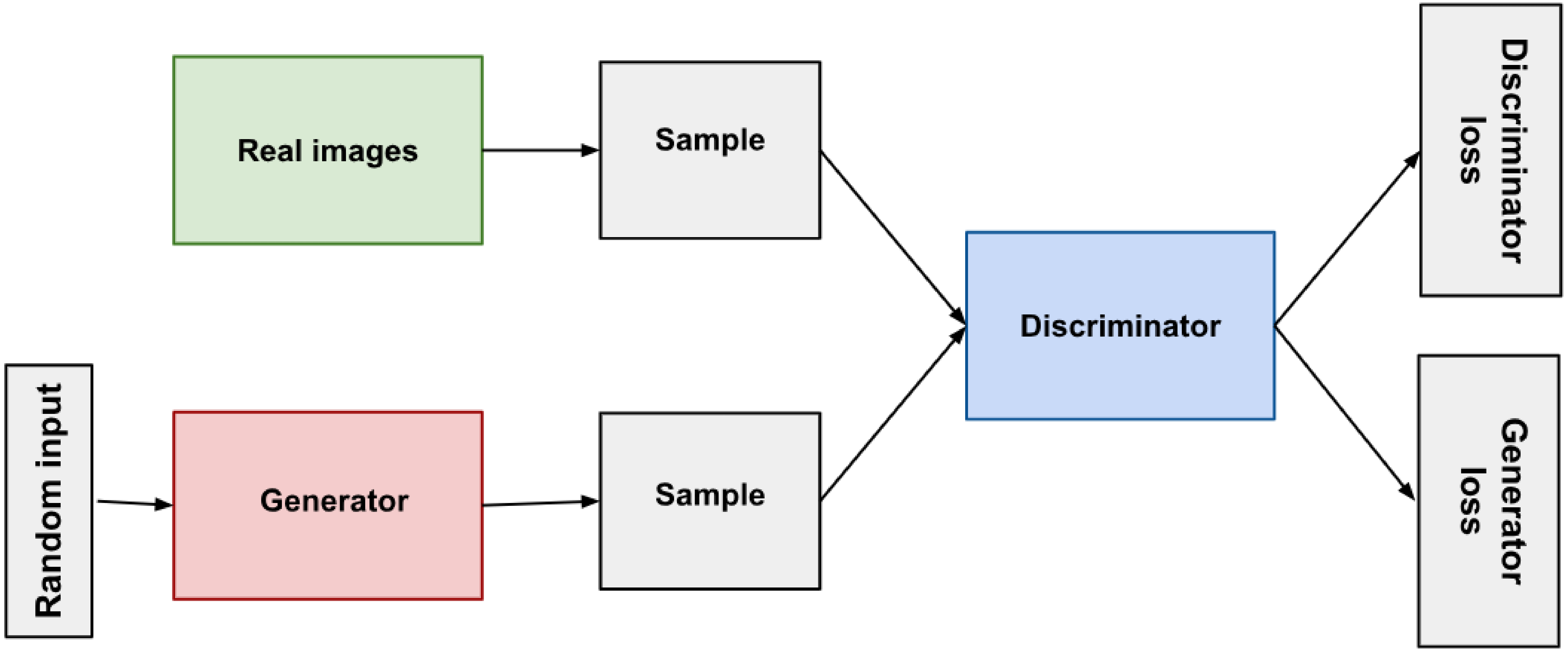


Origins of GANs, GANs, introduced by Ian Goodfellow and his colleagues in 2014.

Definition, GANs are a class of machine learning models that consists of two neural networks, the generator and the discriminator, which are trained adversarially, in a competitive manner

Motivation behind GANs, which aim to generate synthetic data that closely resembles real data distributions.

ARCHITECTURE OF GAN



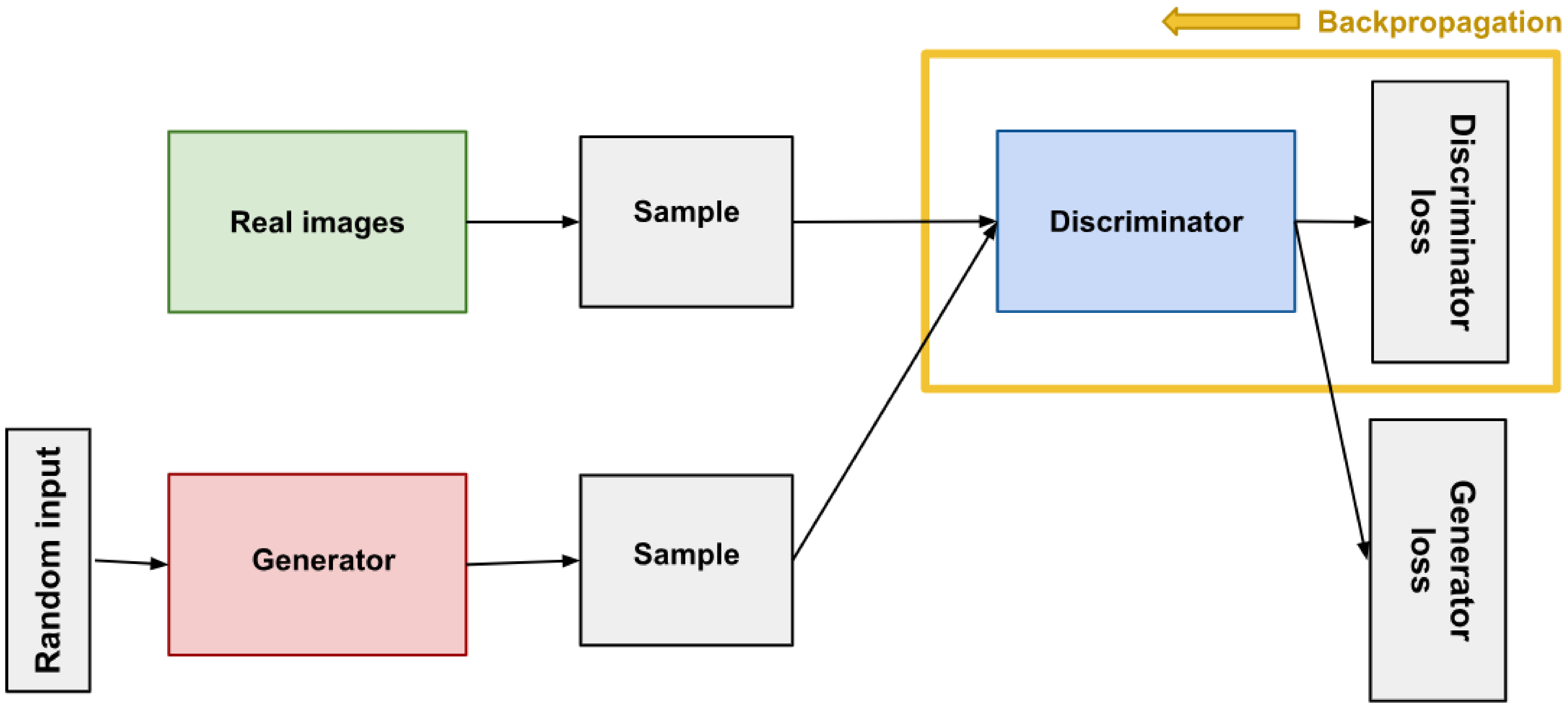
ARCHITECTURE OF GAN

The Generator: Takes random noise as input and transforms it into data samples, typically consists of layers of neural networks, such as convolutional or fully connected layers, output layer generates data samples resembling real data.

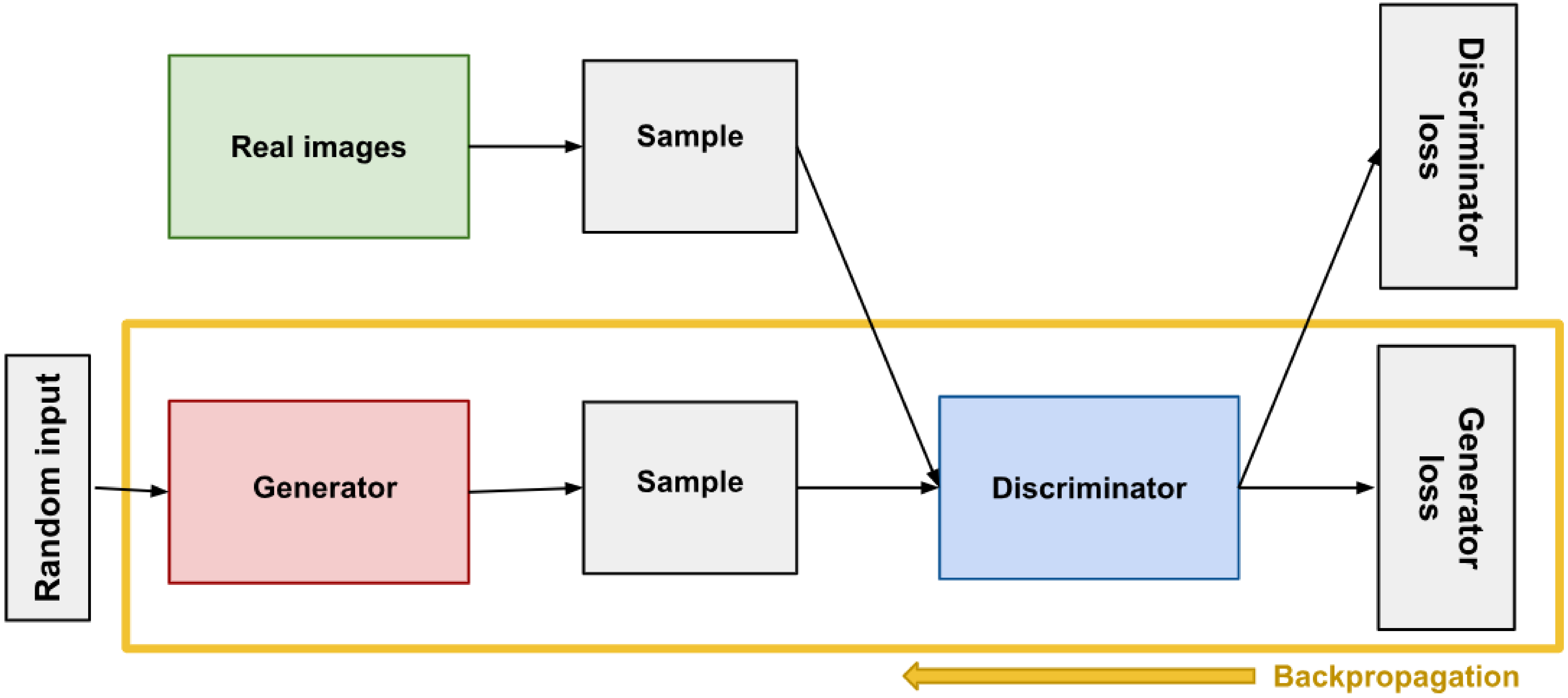
The Discriminator: Distinguishes between real and generated samples from the generator, it is also composed of neural network layers, with an output indicating by assigning probability scores.

Adversarial Training: Generator and discriminator are trained simultaneously in an adversarial manner.

DISCRIMINATOR



GENERATOR



Real images
Sample
Discriminator loss
Random input
Generator
Sample
Discriminator
Generator loss
Backpropagation

GAN TRAINING PROCESS

Discriminator - Keep the generator constant during the discriminator training phase. As discriminator training tries to figure out how to distinguish real data from fake, it has to learn how to recognize the generator's flaws. That's a different problem for a thoroughly trained generator than it is for an untrained generator that produces random output. The discriminator trains for one or more epochs.

Genarator - Keep the discriminator constant during the generator training phase. Otherwise the generator would be trying to hit a moving target and might never converge. The generator trains for one or more epochs.

Repeat steps 1 and 2 to continue to train the generator and discriminator networks..

LOSS FUNCTION

Generator tries to minimize the following function while the discriminator tries to maximize it

$$E_x[log(D(x))] + E_z[log(1 - D(G(z)))]$$

- D(x) is the discriminator's estimate of the probability that real data instance x is real.
- Ex is the expected value over all real data instances.
- G(z) is the generator's output when given noise z.
- D(G(z)) is the discriminator's estimate of the probability that a fake instance is real.
- Ez is the expected value over all random inputs to the generator (in effect, the expected value over all generated fake instances G(z)).
- The formula derives from the cross-entropy between the real and generated distributions.

GAN EVALUATION METRICS:

Precision and Recall

Precision and Recall are used to evaluate how well the generator captures specific features of the data. Let's say the generator is supposed to generate images of cats. Precision tells us how many of the images labeled as cats are actually cats, while Recall tells us how many of the real cat images were correctly identified by the discriminator.

		Predicted	
		0	1
Actual	0	TN	FP
	1	FN	TP

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

GAN EVALUATION METRICS:

Inception Score

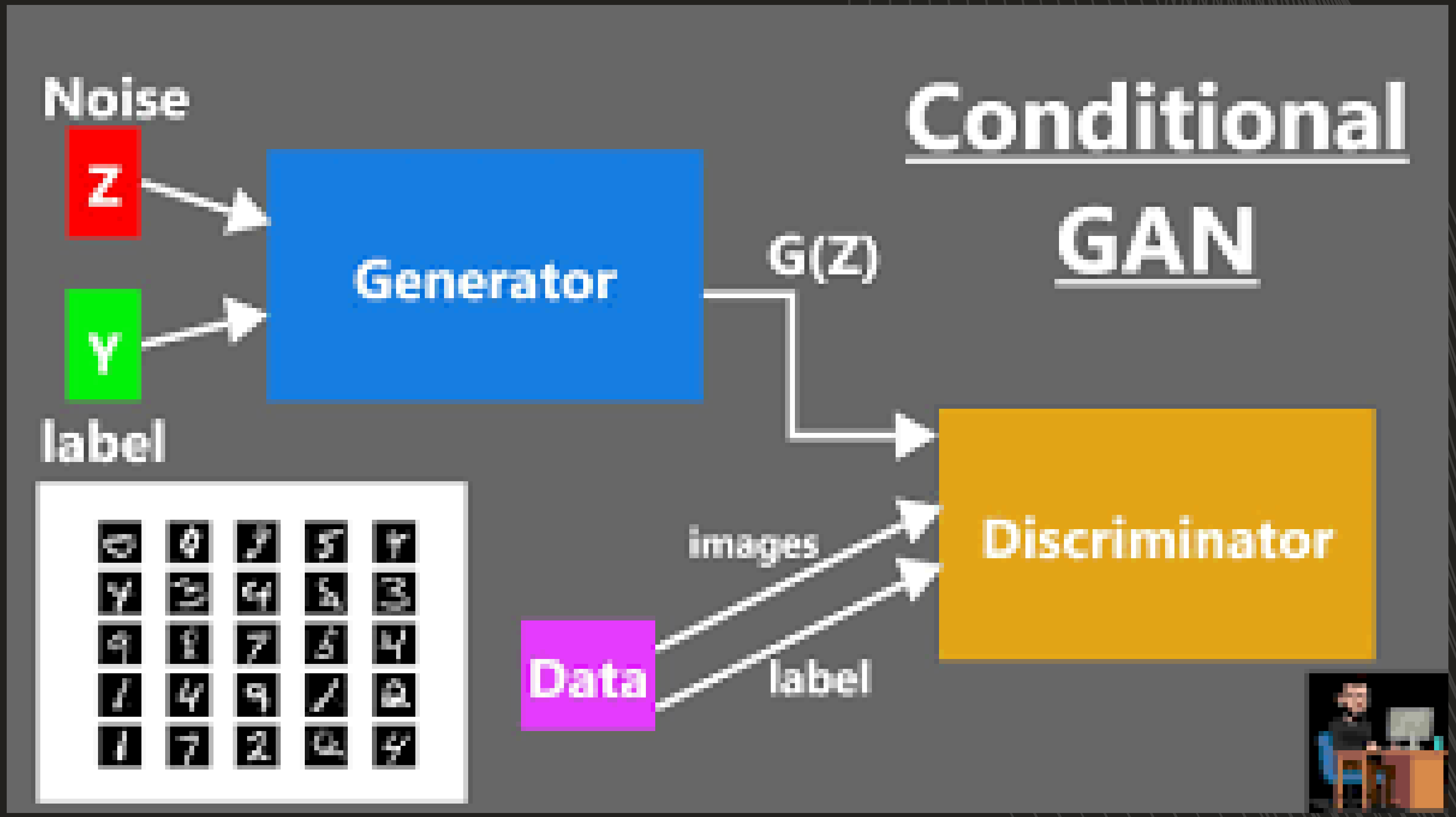
Inception Score evaluates the quality and diversity of the images generated by a GAN. If all generated images look very similar, the Inception Score will be low because the experts are very confident about their predictions and there isn't much diversity.

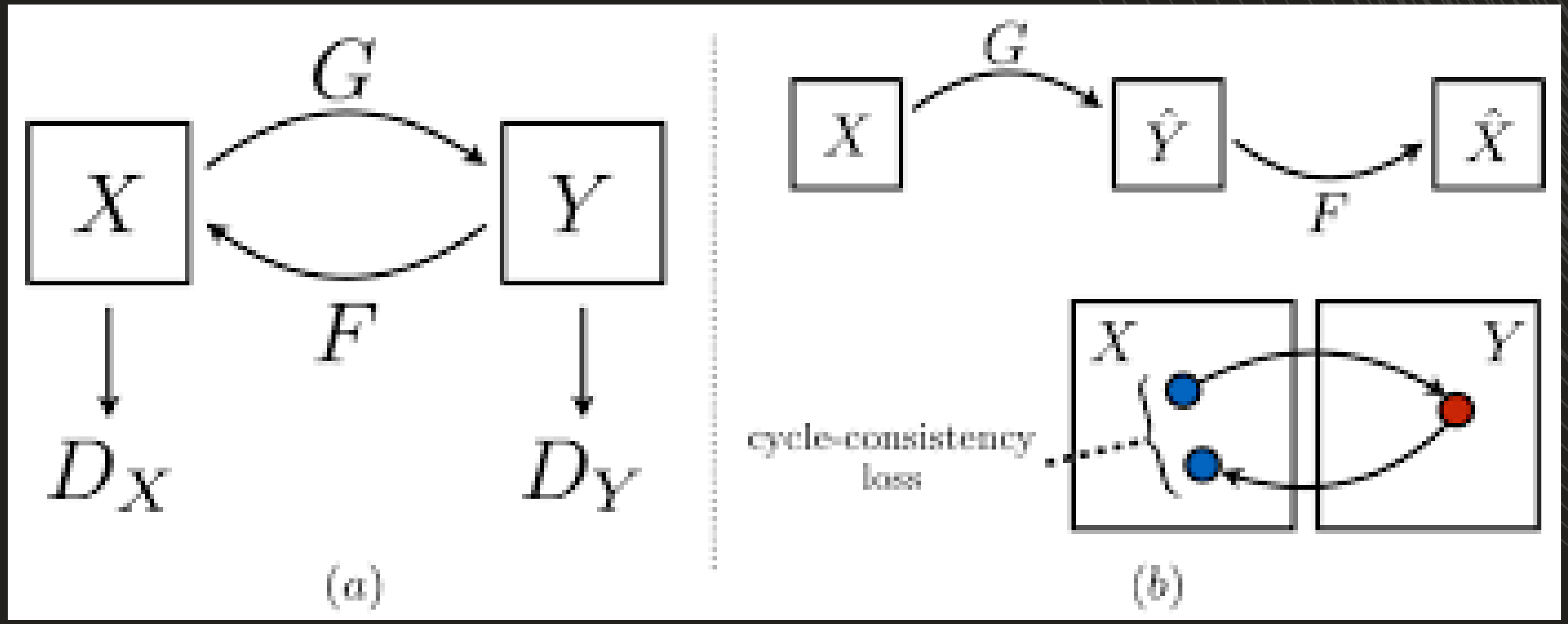
Frechet Inception Distance (FID):

FID compares the distribution of generated images with that of real images. If the distribution of generated images is very similar to that of real images, the FID will be low, indicating that the generated images are very close to real ones.

Variants of GANs

- **CycleGANs:** Perform image-to-image translation tasks.
- **StyleGANs:** Generate high-resolution images with fine-grained style control.
- **Conditional GANs**: Condition generation process on additional information.
- **Wasserstein GANs:** Use Wasserstein distance as training objective for more stable training.
- **InfoGANs:** Learn interpretable latent representations.





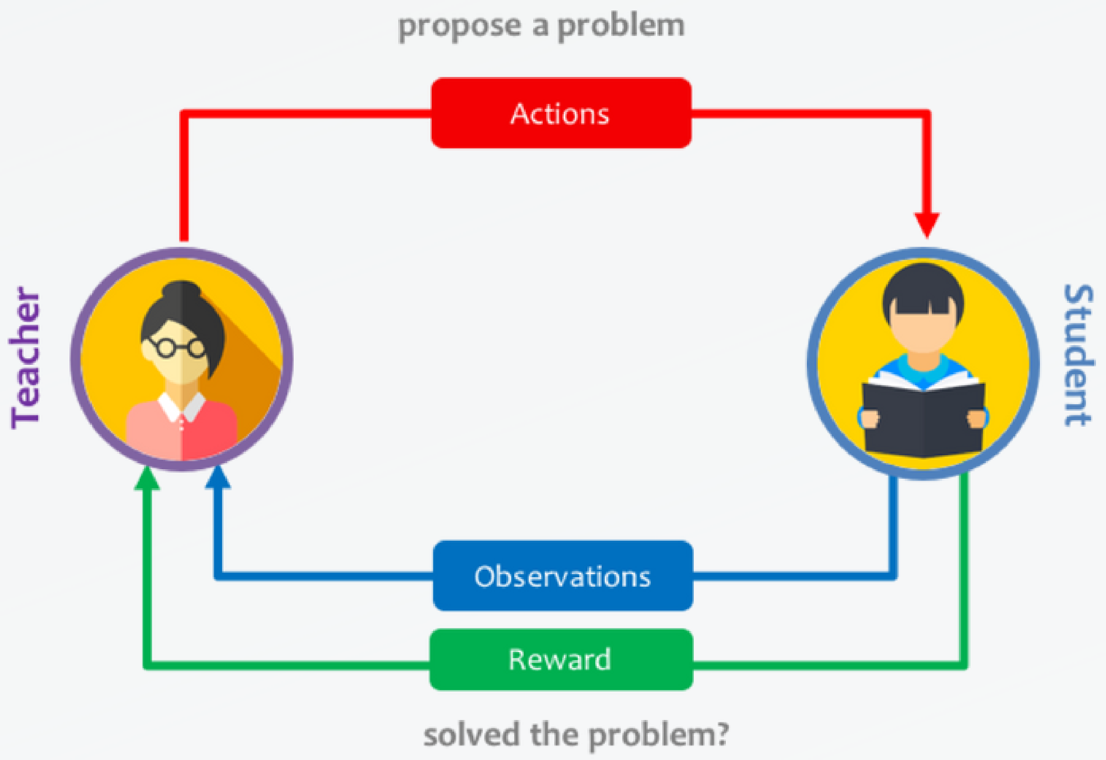
GAN INNOVATIONS

- **Progressive Growing:** Train GANs in stages for high-resolution image generation.
- **Self-Attention Mechanisms:** Capture long-range dependencies in GANs.
- **BigGAN:** High-capacity architecture for generating high-quality images.
- **Unsupervised Representation Learning:** Learn meaningful data representations without supervision.

GAN TRAINING TRICKS AND CHALLENGES

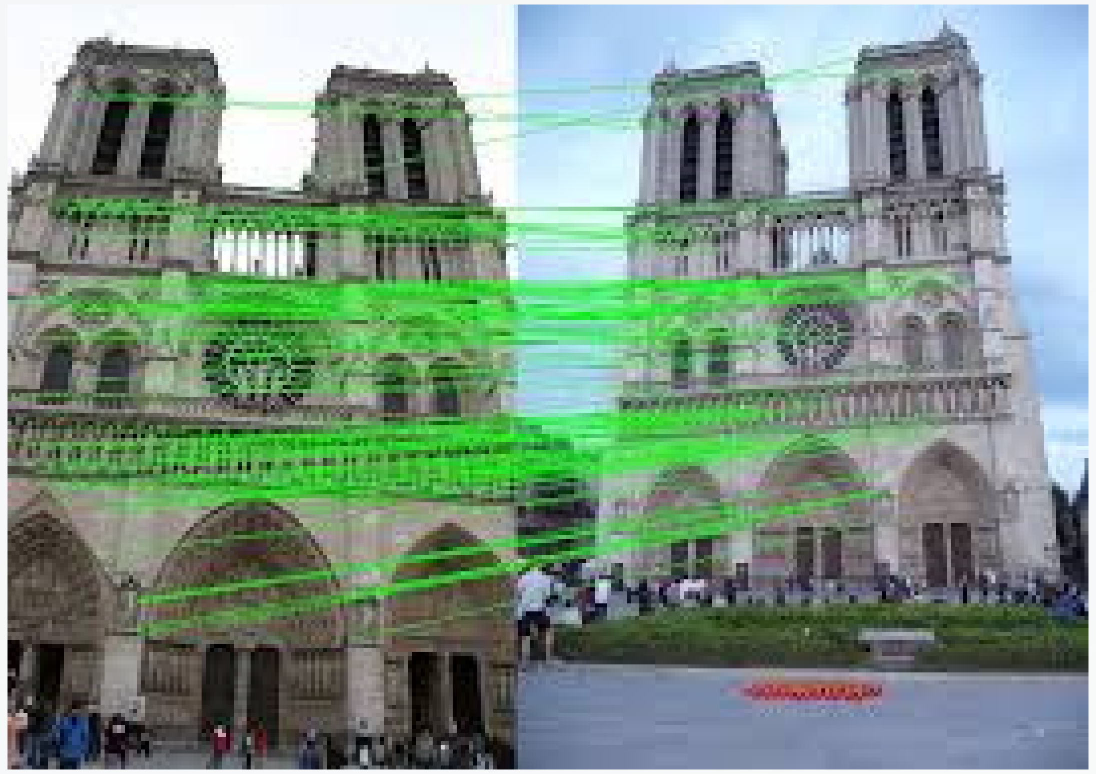
Curriculum Learning

Starting with simpler examples during training and gradually increasing the complexity



Feature Matching

It ensure that the features extracted by the discriminator from real and generated samples are similar



Minibatch Discrimination

increase the diversity of generated samples by encouraging the generator to produce more varied outputs.

APPLICATIONS OF GANS

- **Image Generation:** Generate realistic images of faces, landscapes, and artworks.
- **Style Transfer:** Transfer style from one image to another.
- **Super-resolution:** Enhance resolution of low-resolution images.
- **Data Augmentation:** Generate synthetic data for training machine learning models.
- **Image Inpainting:** Fill in missing parts of images.

APPLICATIONS

GAN IN Computer Vision

- Image generation
- Style transfer
- Image inpainting.

GAN IN NLP

- Text generation,
- Style transfer
- Language translation tasks.

FUTURE DIRECTIONS

Improving Stability: Address challenges like mode collapse and instability in training.

Scaling to Larger Datasets: Develop techniques for training GANs on larger datasets.

Exploring Novel Architectures: Investigate new network architectures and training algorithms, domain adaptation and transfer learning

ETHICAL CONSIDERATIONS AND BIAS

Privacy Concerns

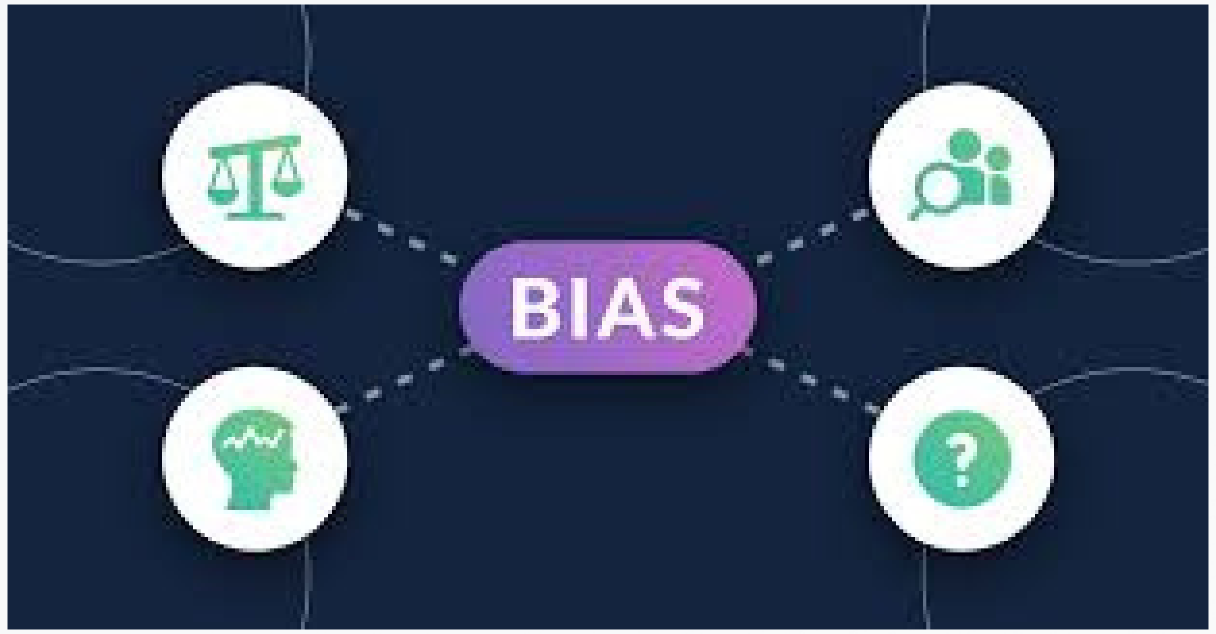
GANs can generate synthetic data that closely resembles real data, raising privacy concerns. There's a risk that personal privacy could be compromised if synthetic data is used inappropriately or leaked.

Deepfake Generation

GANs can create convincing fake videos and images, these deepfakes raise concerns about the potential for misinformation, fraud, and manipulation

Bias in Generated Data

GANs learn from the data they are trained on, which may contain biases present in society. For example, if the training data contains racial or gender biases, the generated data may reflect and reinforce these biases.



CONCLUSION

- GANs have revolutionized the field of generative modeling and found applications in various domains.

- Despite challenges and ethical considerations, GANs continue to drive innovation in machine learning and artificial intelligence.

THANK YOU!