Generative Adversarial Networks

By

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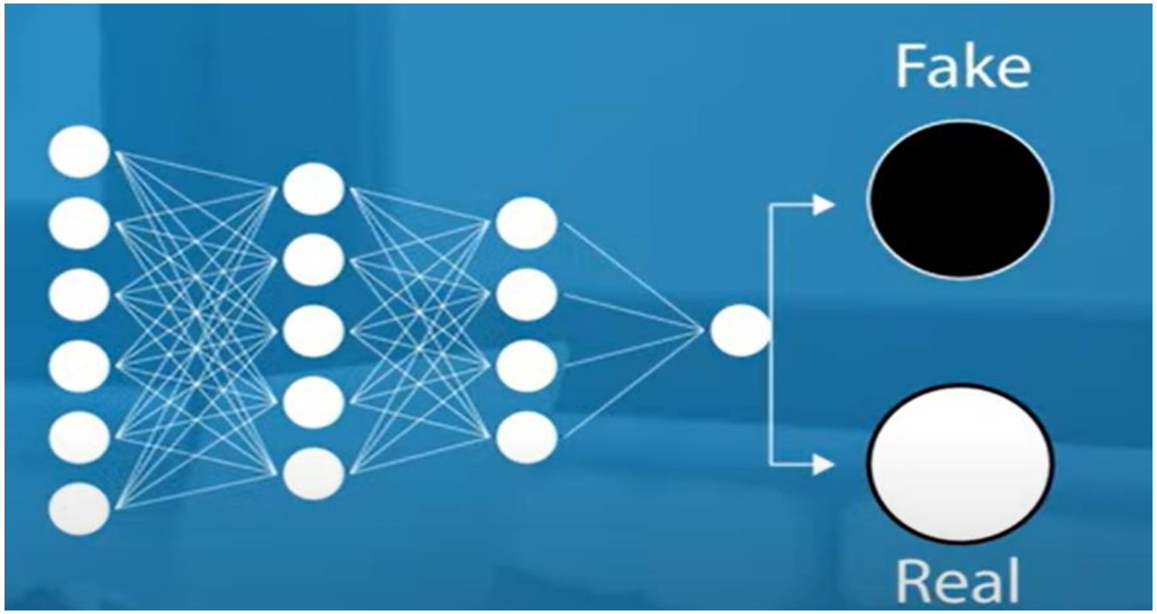
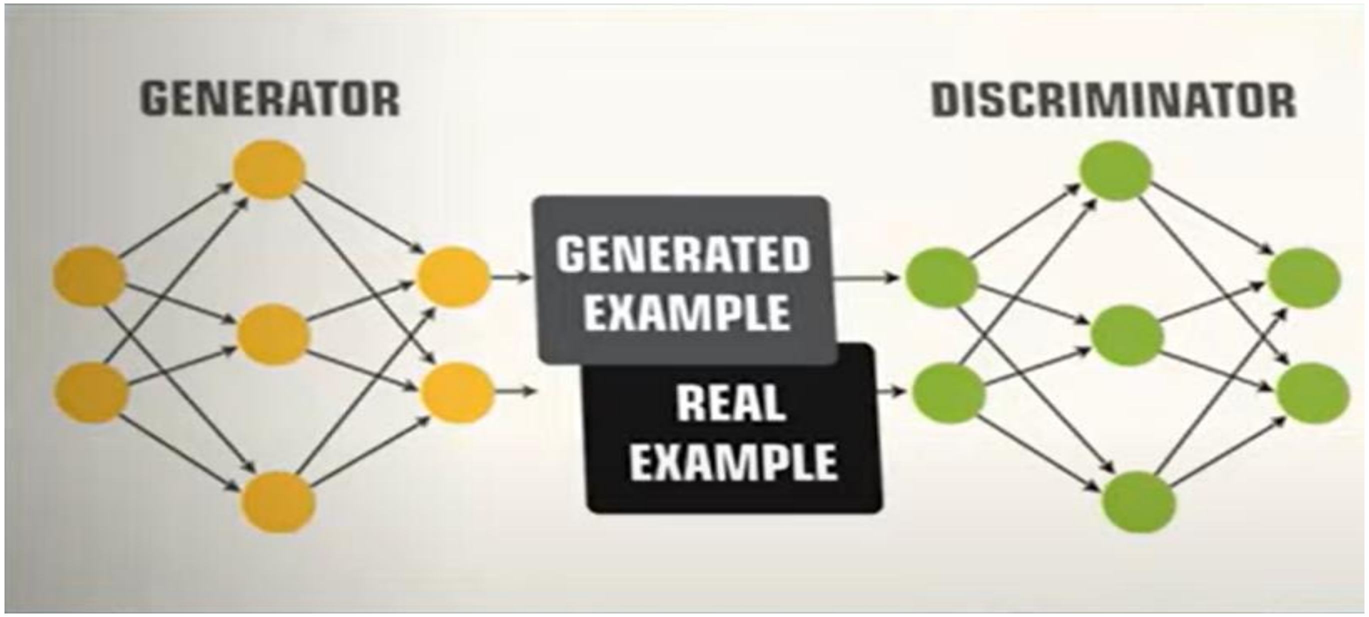
https://realpython.com/generative-adversarial-networks/

Outline

- What are Generative Adversarial Networks
- Generator
- Discriminator
- How GANs work
- Types of GANs
- Application of GANs





What is a GAN?

- ❑ **What is a GAN?**

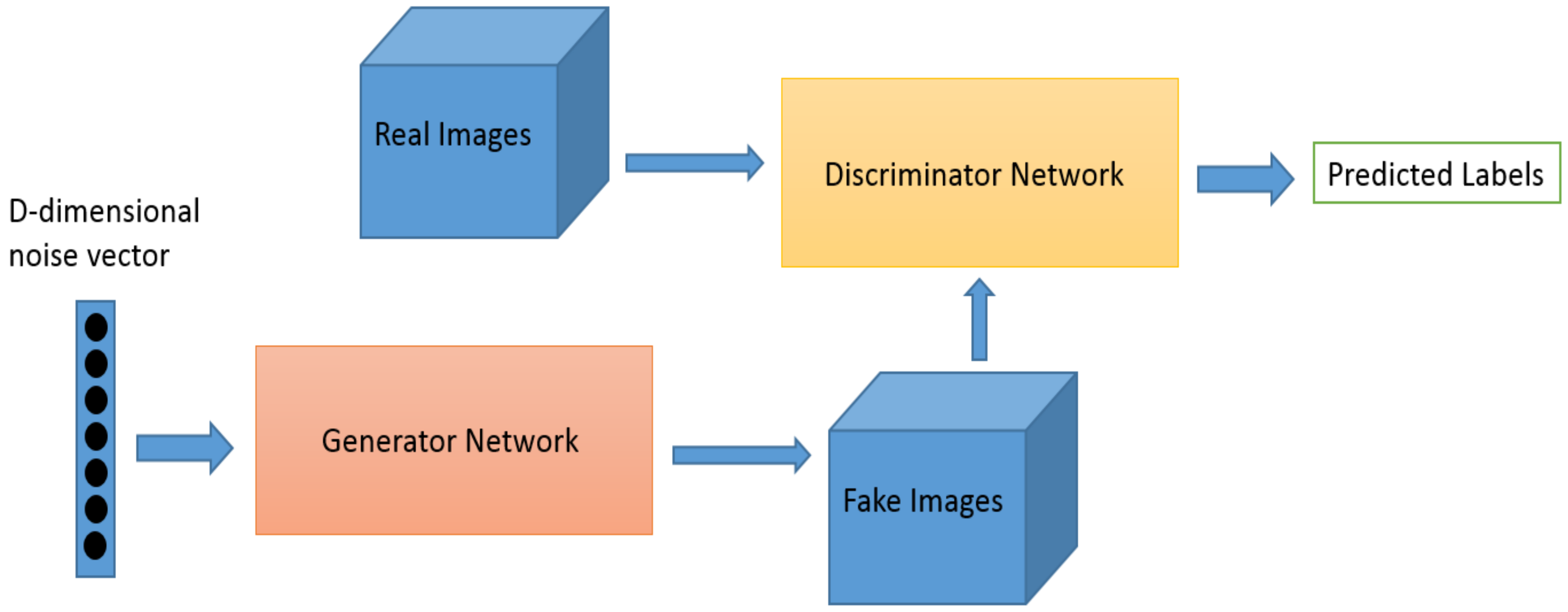
Generative Adversarial Network is an architecture for training a generative model. It was developed and introduced by **Ian J. Goodfellow in 2014**.

- ❑ **The architecture is comprised of two models:**
  - o Generator
  - o Discriminator

- ➢ GANs are neural networks that learn to create duplicate data similar to a known input data.
- ➢ GAN has two components with competing objectives that work through opposite goals.
- ➢ The generator tries to produce perfect data and the discriminator tries to find the defection in the data generated by the generator.

What is a GAN?

- Generative adversarial networks consist of two models: a **generative model** and a **discriminative model**.



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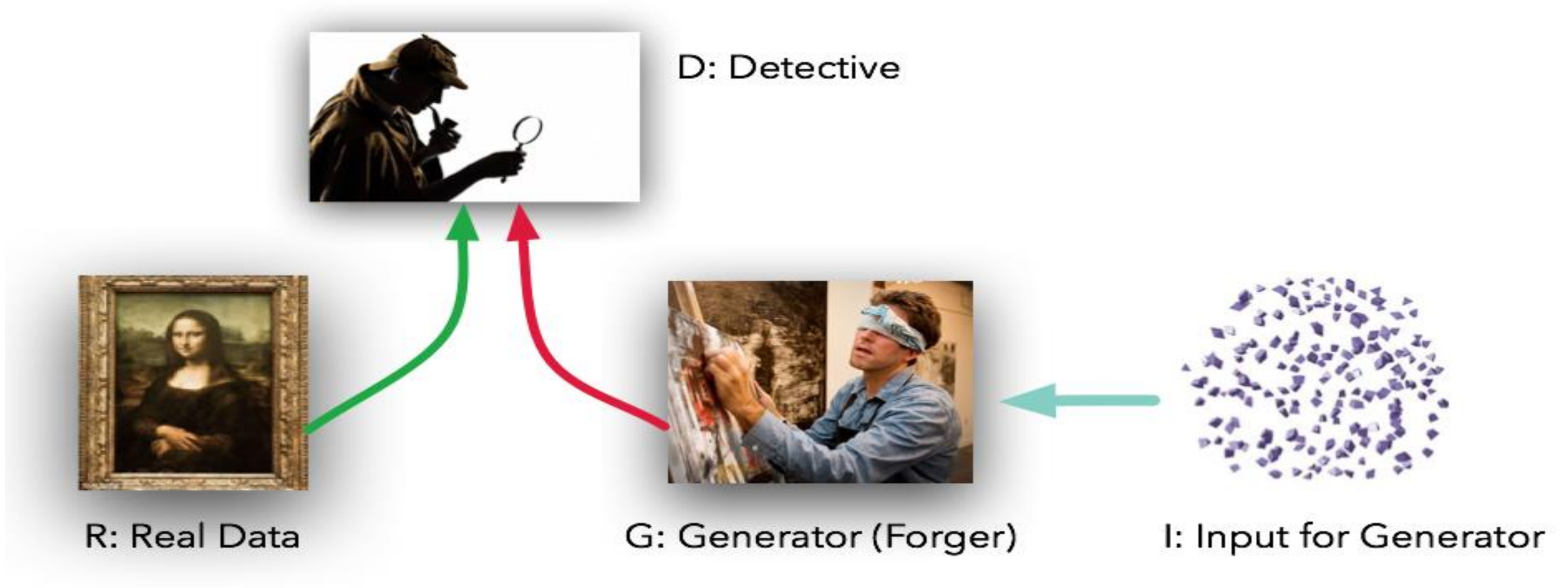
What is a GAN?

- **The discriminator model is a classifier** that has the task of determining whether a given image looks natural (an image from the dataset) or looks like it has been artificially created.
- This is basically **a binary classifier** that will take the form of a **normal convolutional neural network (CNN).**
- The generator model takes random input values and transforms them into images through a deep convolutional neural network.



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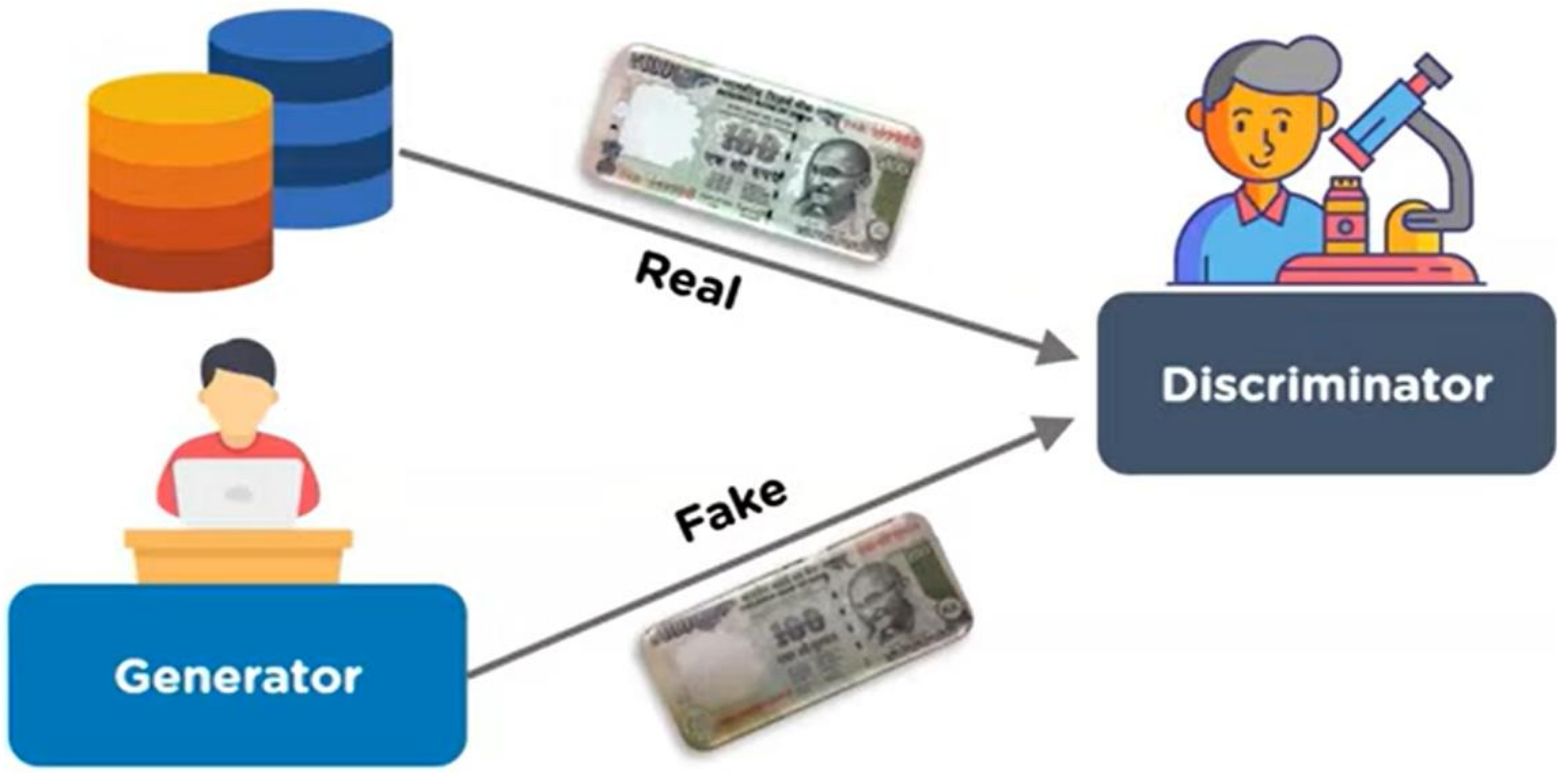
What are Generative Adversarial Networks?

Generative Adversarial Networks consist of two models that **compete to analyze, capture and copy the variations within a dataset.**



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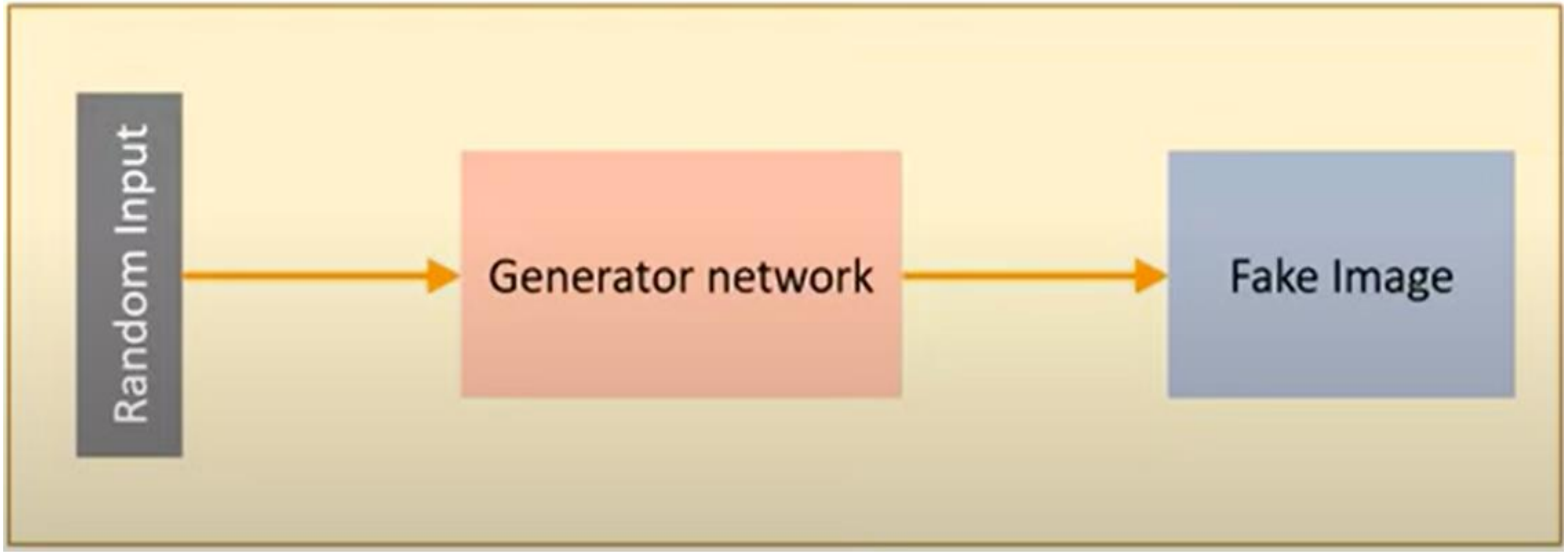
Generator

Generator Network that takes a sample and generates a sample of data.

The Generator in GAN learns to create fake data by incorporating feedback from the Discriminator.



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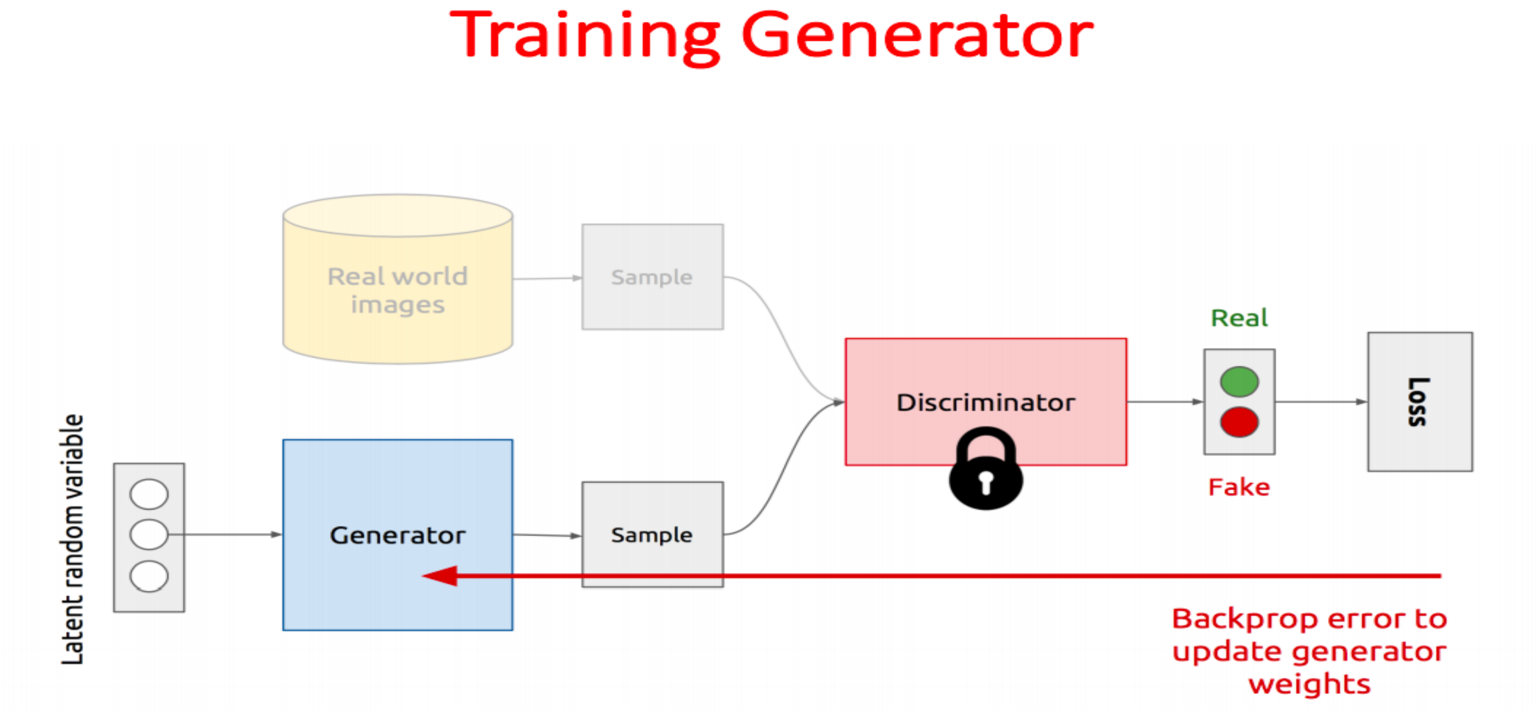
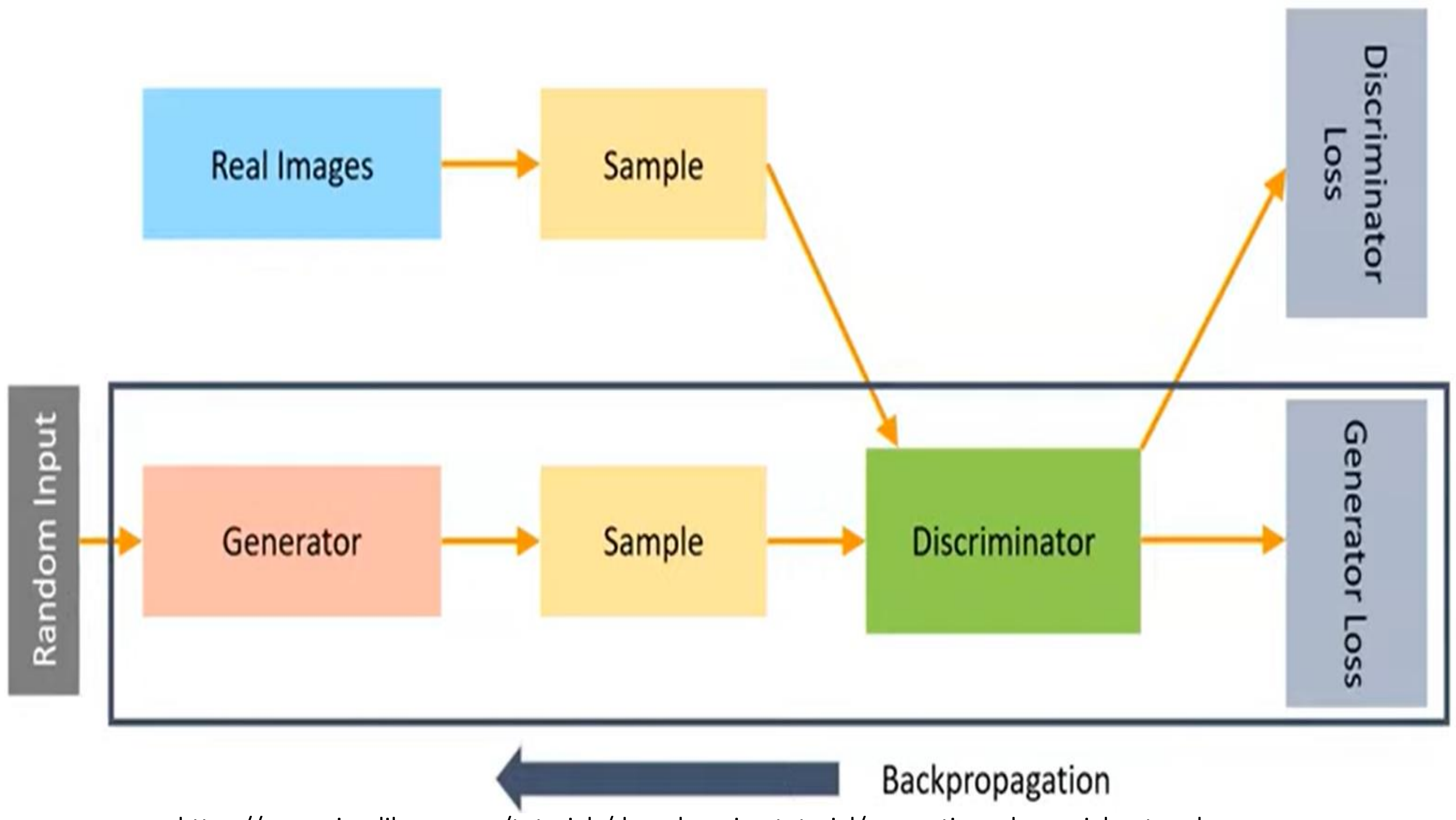
Generator Training

- The Generator is trained while the Discriminator is idle.
- After the Discriminator is trained by the generated fake data of the Generator, we can use its predictions to update the weights for Generator and make it smarter at fooling the Discriminator.



Generator Training



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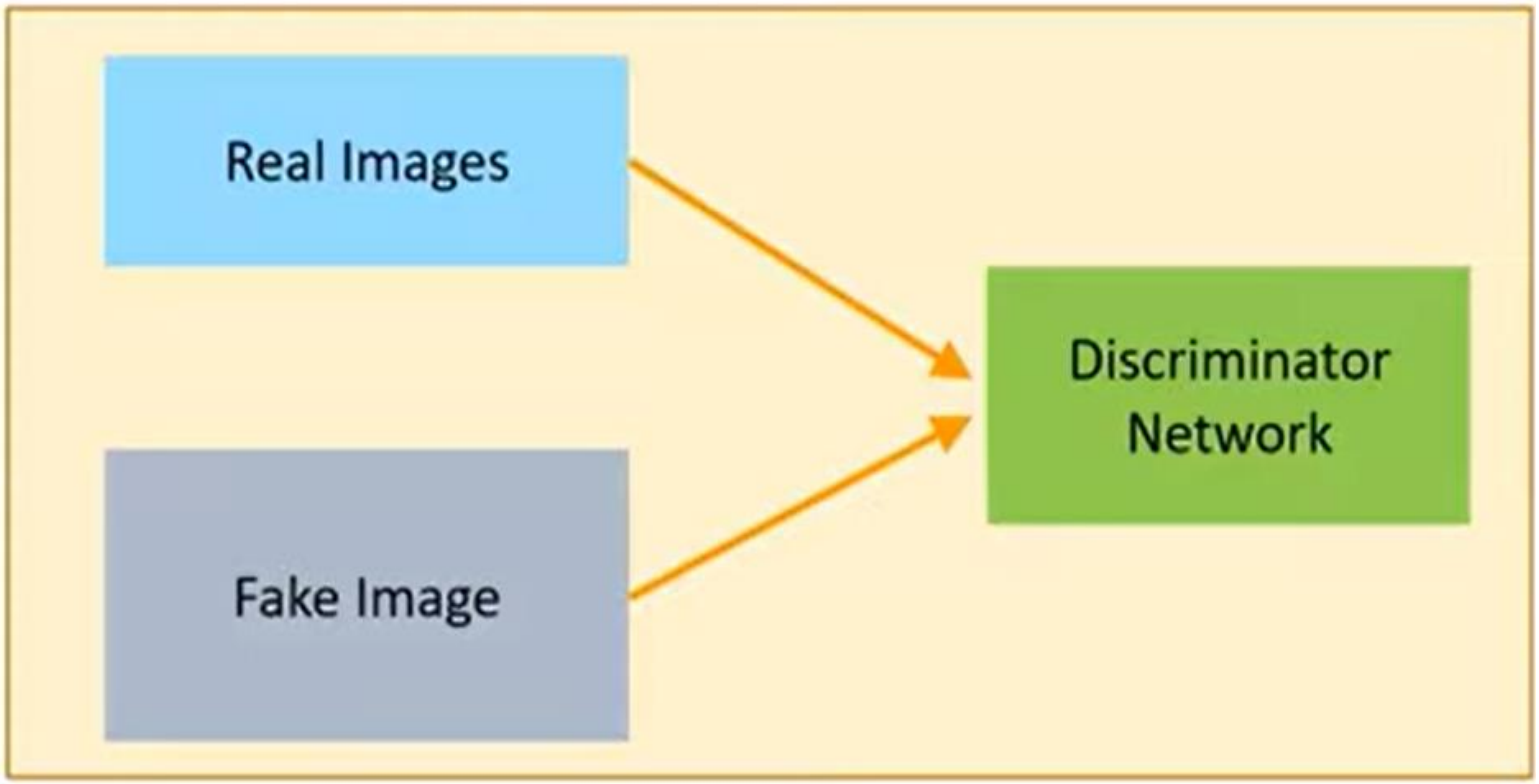
Discriminator

The Discriminator in GAN is a classifier that identifies real data from the fake data created by the Generator.



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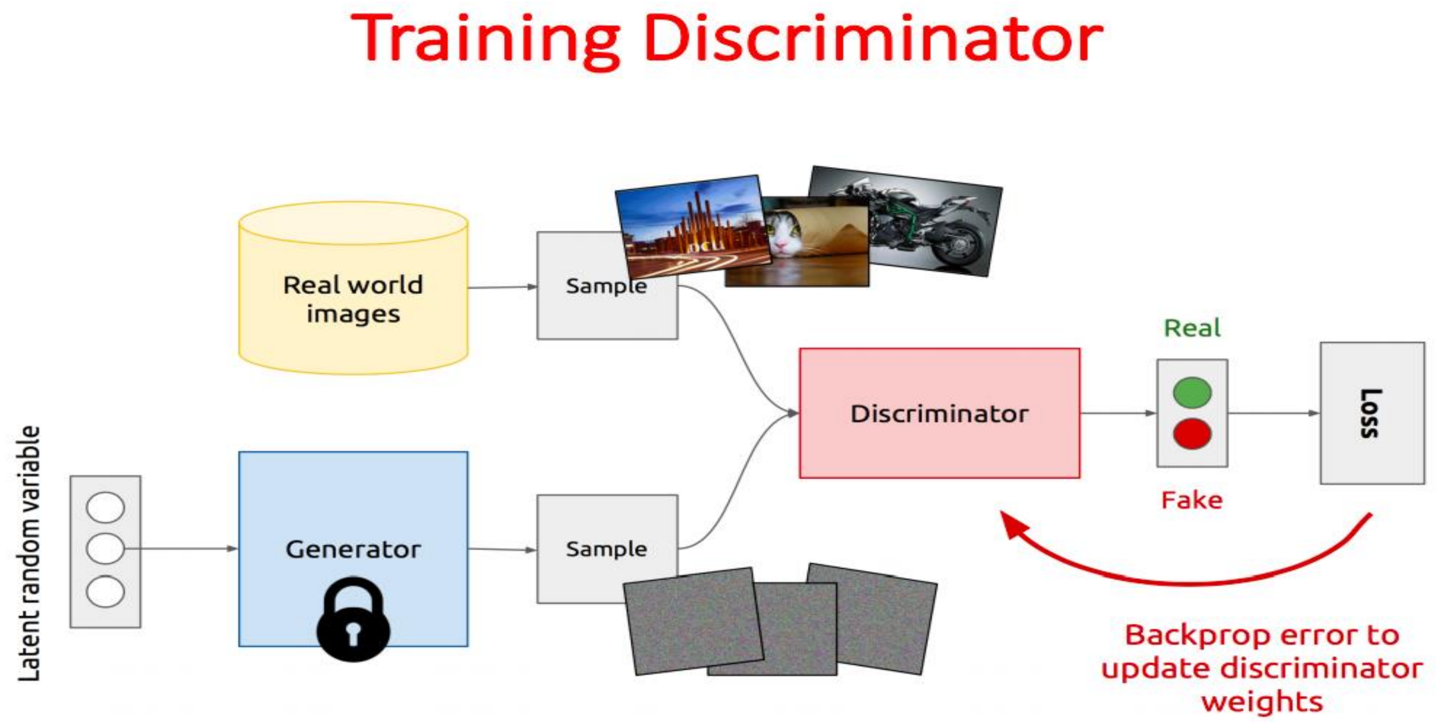
Discriminator Training

- The **Discriminator is trained** while **the Generator is idle.** In this phase, the network is **only forward propagated, and no back-propagation is done.**
- The Discriminator is trained on both the real data and the fake generated data from Generator for n epochs and see if it can correctly predict them as real and fake respectively.



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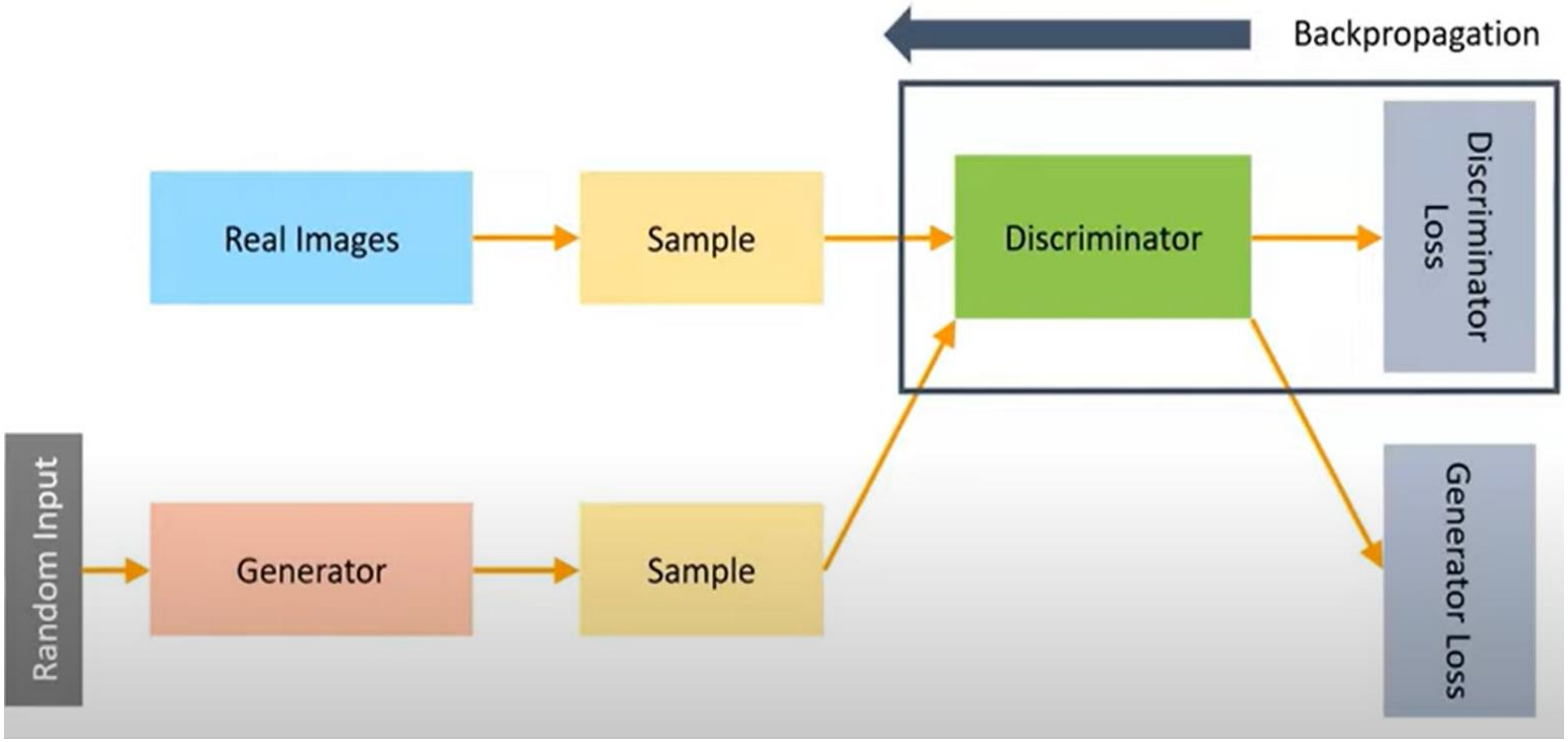
Discriminator Training



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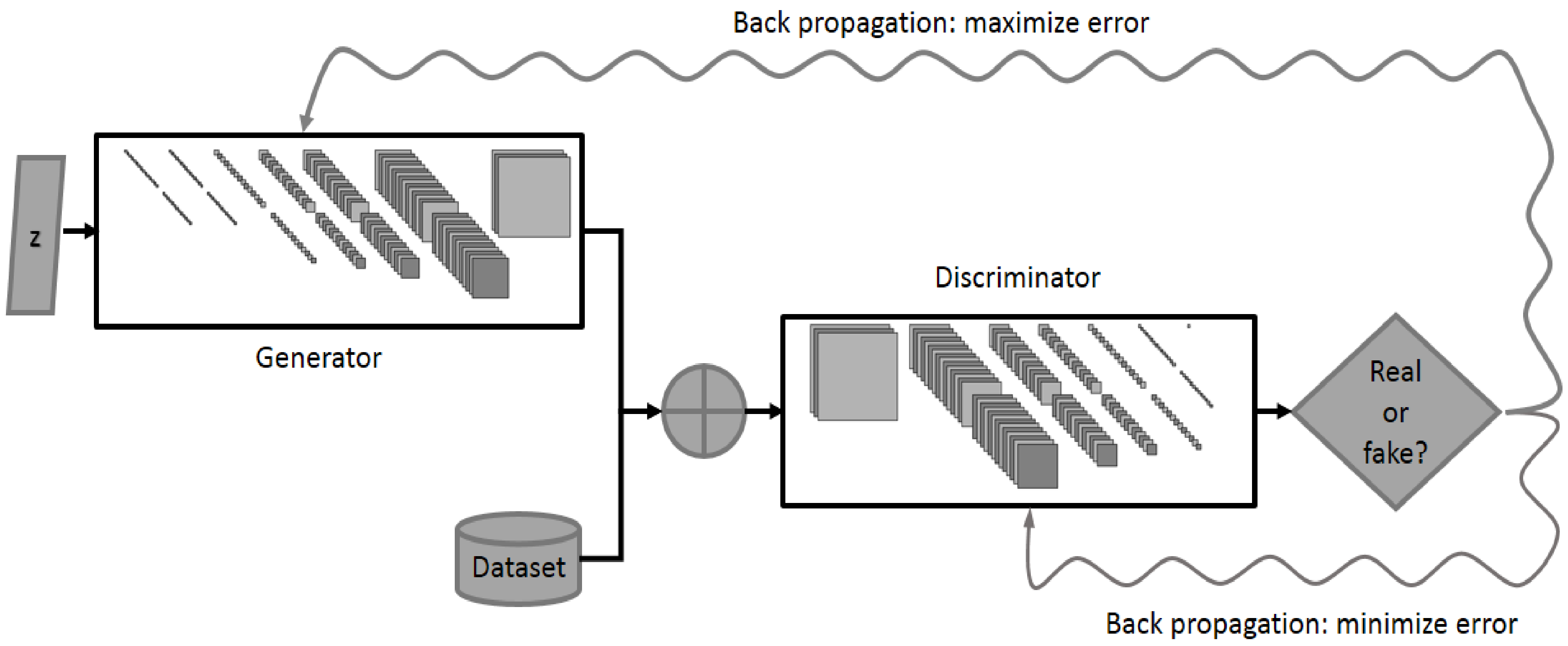
How Does GANs Work?

The Discriminator estimates the probability that the sample it got is from the training data and not from the Generator.


Back propagation: maximize error
z
Generator
Discriminator
Real or fake?
Dataset
Back propagation: minimize error

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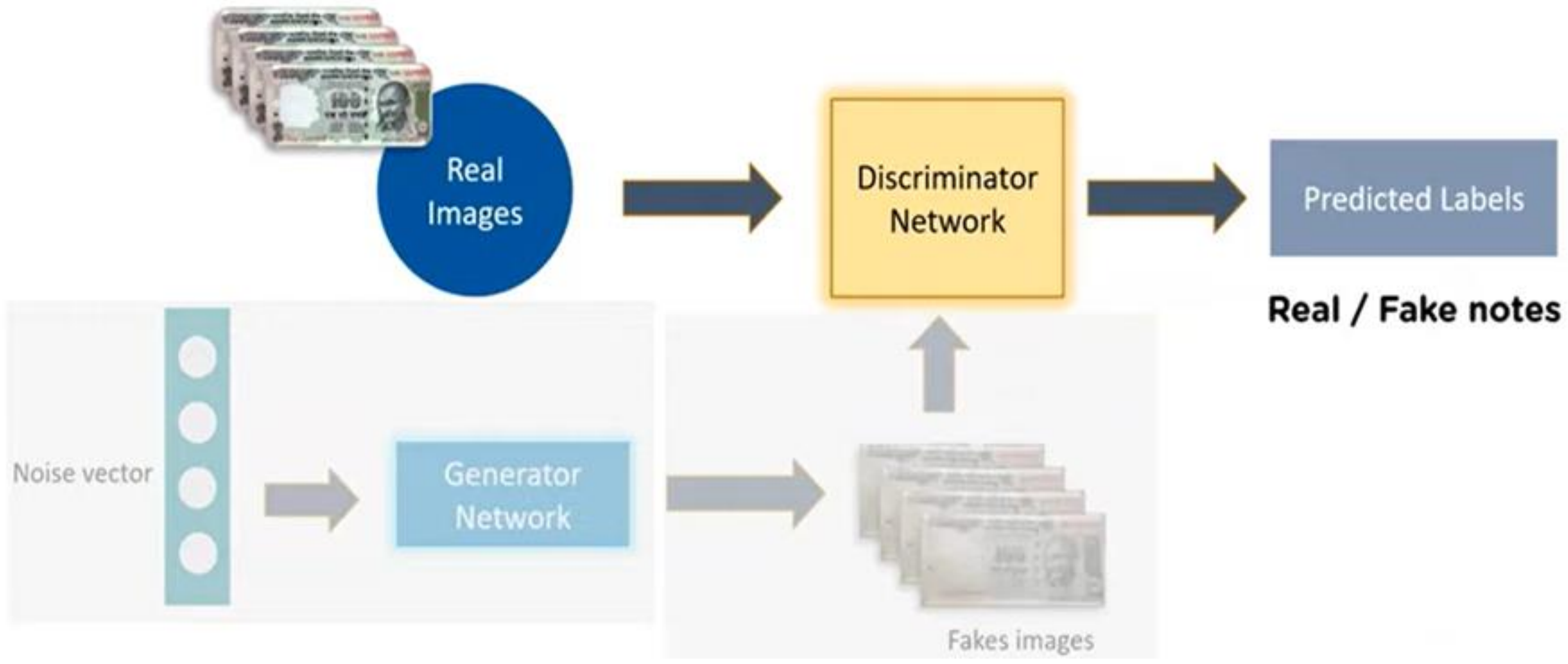
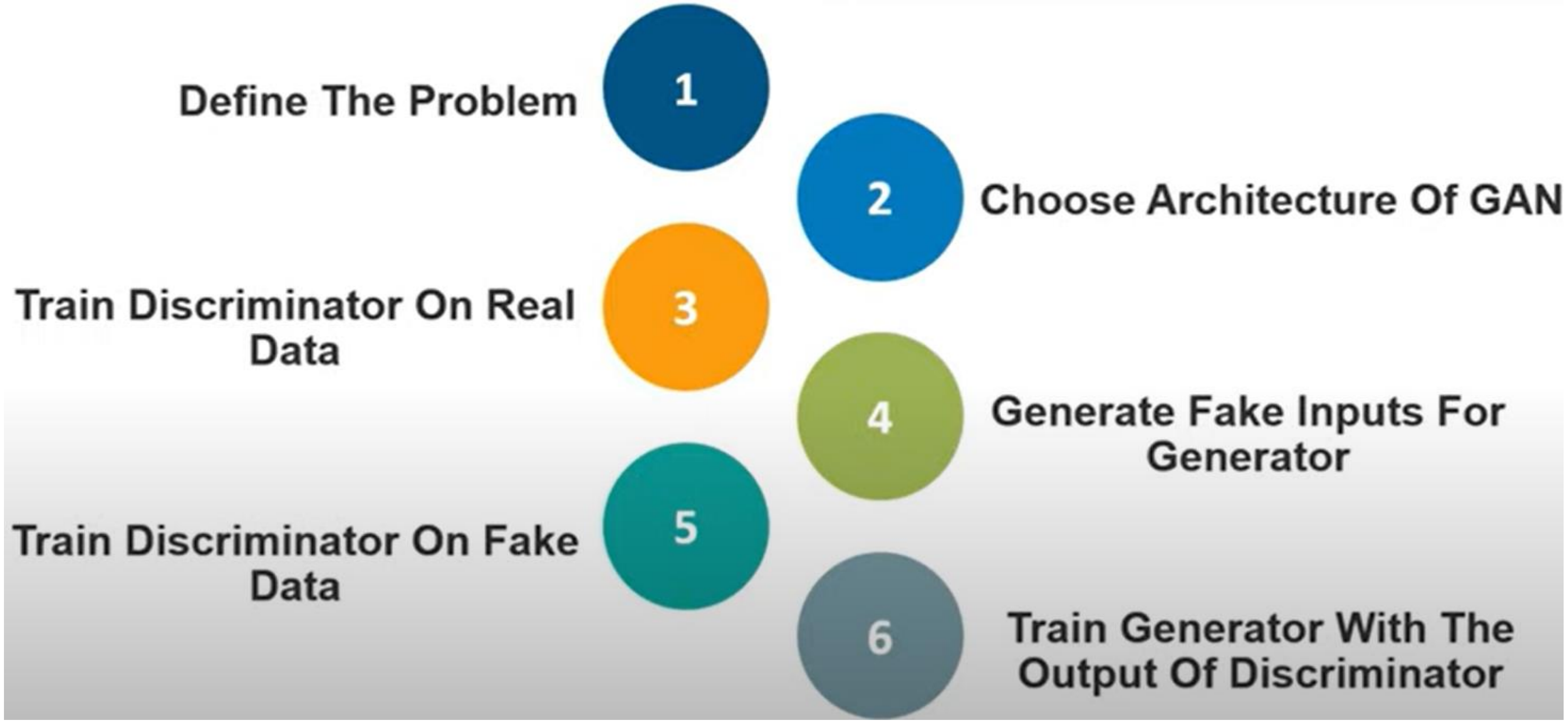
How GANs Work?



How GANs Work?

Steps for training GA-

1. Define the Problem
2. Choose the architecture of GAN
3. Train Discriminator on Real Data
4. Generate Fake input for Generator
5. Train Discriminator on Fake data
6. Train Generator with the output of Discriminator.


Define The Problem
1
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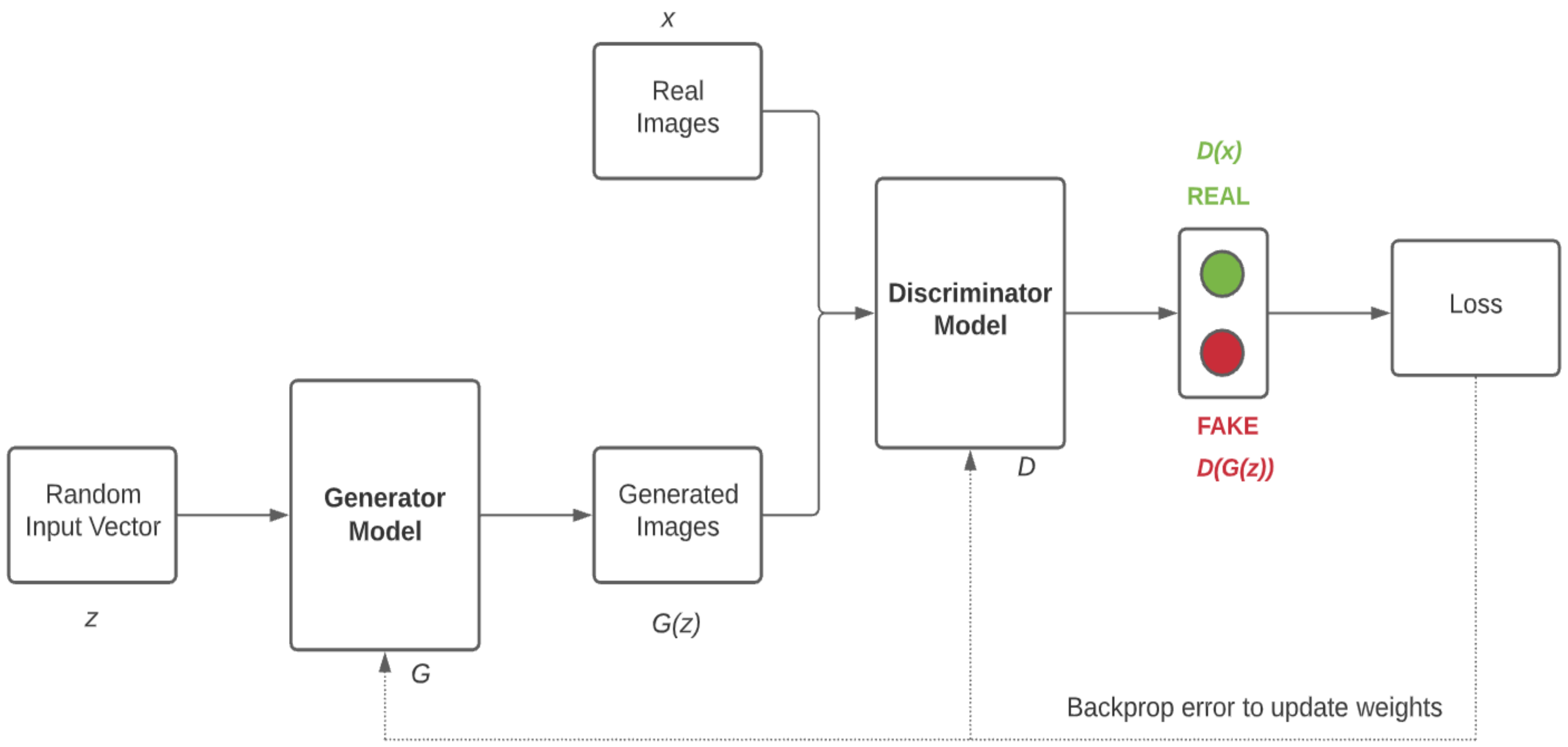
How GANs Work?



How GANs Work?

- The **Generator Model *G*** takes **a random input vector *z* as an input** and **generates the images *G(z)*.**
- These **generated images** along with **the real images *x* from training data** are **then fed to the Discriminator Model *D*.**
- The **Discriminator Model** then **classifies the images as real or fake.**
- Then, we have to **measure the loss and this loss has to be back propagated to update the weights of the Generator and the Discriminator.**
- When we are **training the Discriminator, we have to freeze the Generator** and **back propagate errors to only update the Discriminator.**
- When we are **training the Generator, we have to freeze the Discriminator** and **back propagate errors to only update the Generator.**

How GANs Work?

Thus, the Generator Model and the Discriminator Model getting better and better at each epoch.

We have to stop training when it attains the *D(x)* = *0.5* *for all x*. In simple words, **when the generated images look almost like real images.**

How GANs Work?

The mathematical formula for working on GANs can be represented as:-

It is designed to quantify the difference between the two probability distributions.

$$V(D, G) = E_{x\sim Pdata(x)}[\log D(x)] + E_{z\sim p(z)}[\log(1 - D(G(z)))]$$

Where,
G = Generator
D = Discriminator
Pdata(x) = Distribution of real data
p(z) = Distribution of Generator
X = Sample from Pdata(x)
z = Sample from p(z)
D(x) = Discriminator Network
G(z) = Generator Network

How GANs Work?

*Note: The term $E_{x\sim pdata(x)}$ [log D(x)] can be read as **E of log(D(x)) when x is sampled from p_{data}(x)** and similar for the second term.*

In the equation, **the Generator wants to minimize the V(D, G)** whereas the **Discriminator wants to maximize the V(D, G). Let us understand both terms:**

Ex~pdata(x) [log D(x)]: Average log probability of D when real image is input.

Ez~pz(z) [log(1 – D(G(z)))]: Average log probability of D when the generated image is input.

Derivation of the Loss Function

The loss function described in the original paper by **Ian Goodfellow et al.** can be derived from the formula of binary cross-entropy loss. The **binary cross-entropy loss** can be written as

$$L(\hat{y}, y) = [y.log\hat{y} + (1 - \underset{\underset{\text{Original data}}{\uparrow}}{y}).log(1 - \underset{\underset{\text{Reconstructed data}}{\uparrow}}{\hat{y}})]$$

Discriminator Loss

$$L(\hat{y}, y) = [y.log\hat{y} + (1 - \underset{\text{Original data}}{\underset{\uparrow}{\boxed{y}}}).log(1 - \underset{\text{Reconstructed data}}{\underset{\uparrow}{\boxed{\hat{y}}}})]$$

While training discriminator, the label of data coming from $P_{data}(x)$ is $y = 1$ (real data) and $\hat{y} = D(x)$. Substituting this in above loss function we get,

$$L(D(x), 1) = log(D(x)) \tag{1}$$

and for data coming from generator, the label is $y = 0$ (fake data) and $\hat{y} = D(G(z))$. So in this case,

$$L(D(G(z)), 0) = log(1 - D(G(z))) \tag{2}$$

Now, **the objective of the discriminator is to correctly classify the fake and real dataset.** For this, **equations (1) and (2) should be maximized** and **final loss function for the discriminator** can be given as,

$$L^{(D)} = \max[log(D(x)) + log(1 - D(G(z)))] \tag{3}$$

Generator Loss

Here, the generator is competing against discriminator. So, it will try to minimize the equation (3) and loss function is given as,

$$L^{(G)} = \min[log(D(x)) + log(1 - D(G(z)))] \tag{4}$$

Combined Loss Function-MinMax Loss Function

We can combine equations (3) and (4) and write as,

$$L = \min_G \max_D [log(D(x)) + log(1 - D(G(z)))] \tag{5}$$

The above loss function is valid only for a single data point, to consider entire dataset we need to take the expectation of the above equation as

$$\min_G \max_D V(D,G) = \min_G \max_D \left(E_{x \sim P_{data}(x)}[logD(x)] + E_{z \sim P_z(z)}[log(1 - D(G(z)))]\right) \tag{6}$$

which is the same equation as described in the original paper by Goodfellow et al.

Loss Function

The loss function tells how good your model is in predictions.

If the **model predictions are closer to the actual values the Loss will be minimum** and **if the predictions are totally away from the original values the loss value will be the maximum.**

Loss= abs(Y_pred – Y_actual)

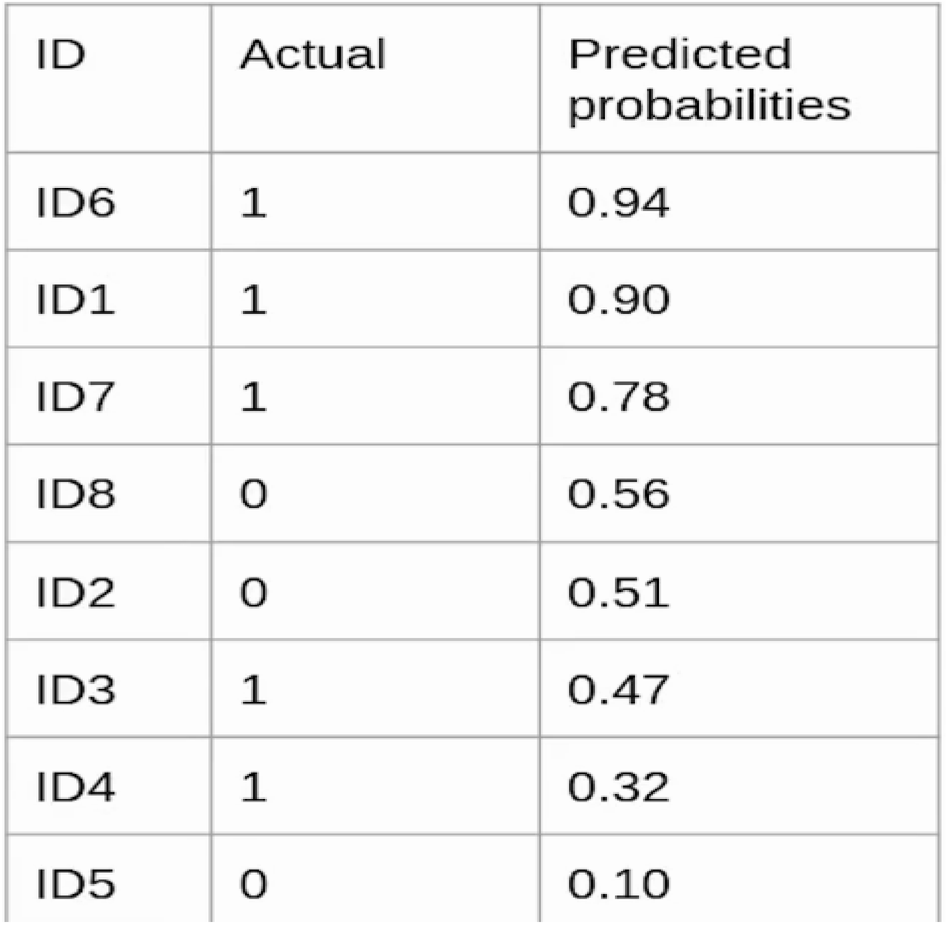
What is Binary Cross Entropy Or Logs Loss?

Binary Cross Entropy compares each of the predicted probabilities to actual class output which can be either 0 or 1.

It then calculates the score that penalizes the probabilities based on the distance from the expected value.

That means how close or far from the actual value.

Predicted Probabilities



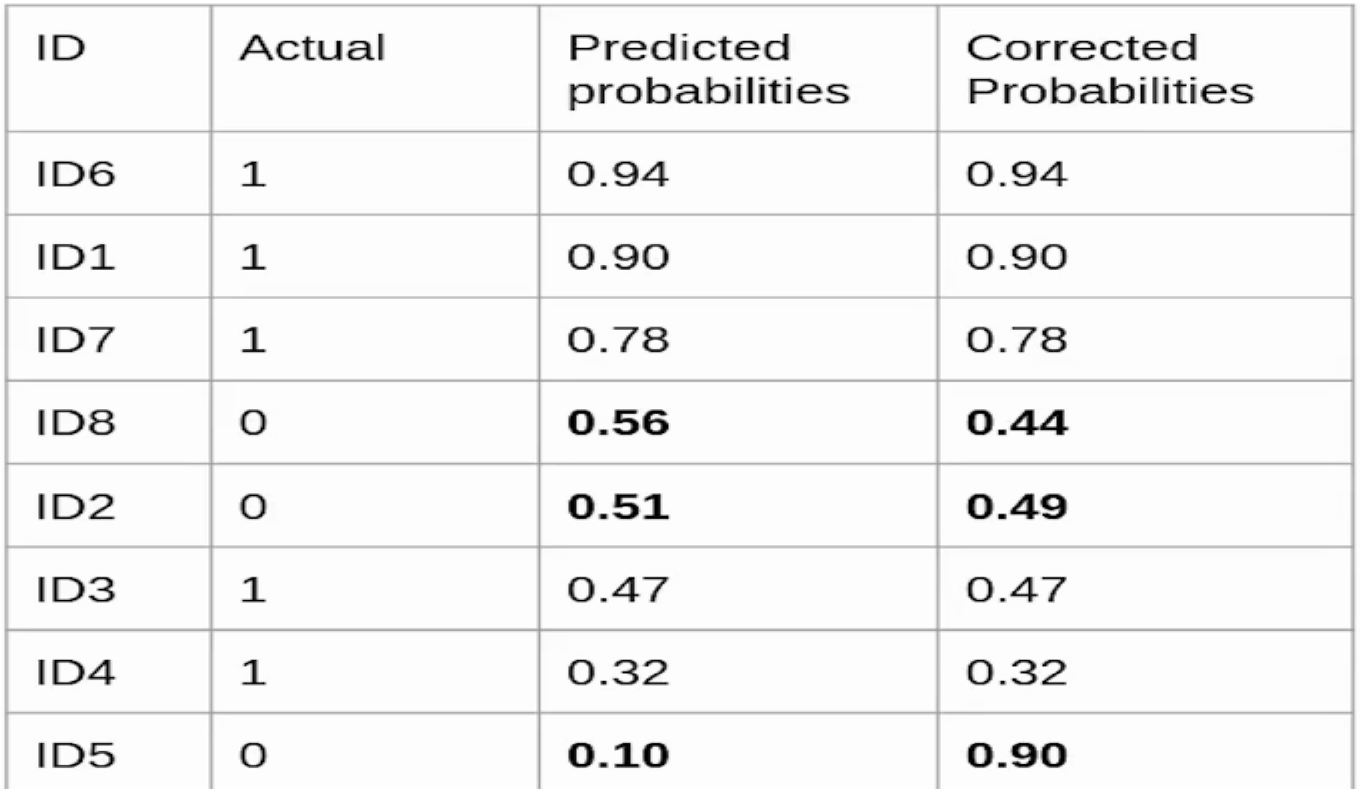
ID	Actual	Predicted probabilities
ID6	1	0.94
ID1	1	0.90
ID7	1	0.78
ID8	0	0.56
ID2	0	0.51
ID3	1	0.47
ID4	1	0.32
ID5	0	0.10

ID: It represents a unique instance.

Actual: It is the class the object originally belongs to.

Predicted probabilities.: The is output given by the model that tells, the probability object belongs to class 1.

Corrected Probabilities

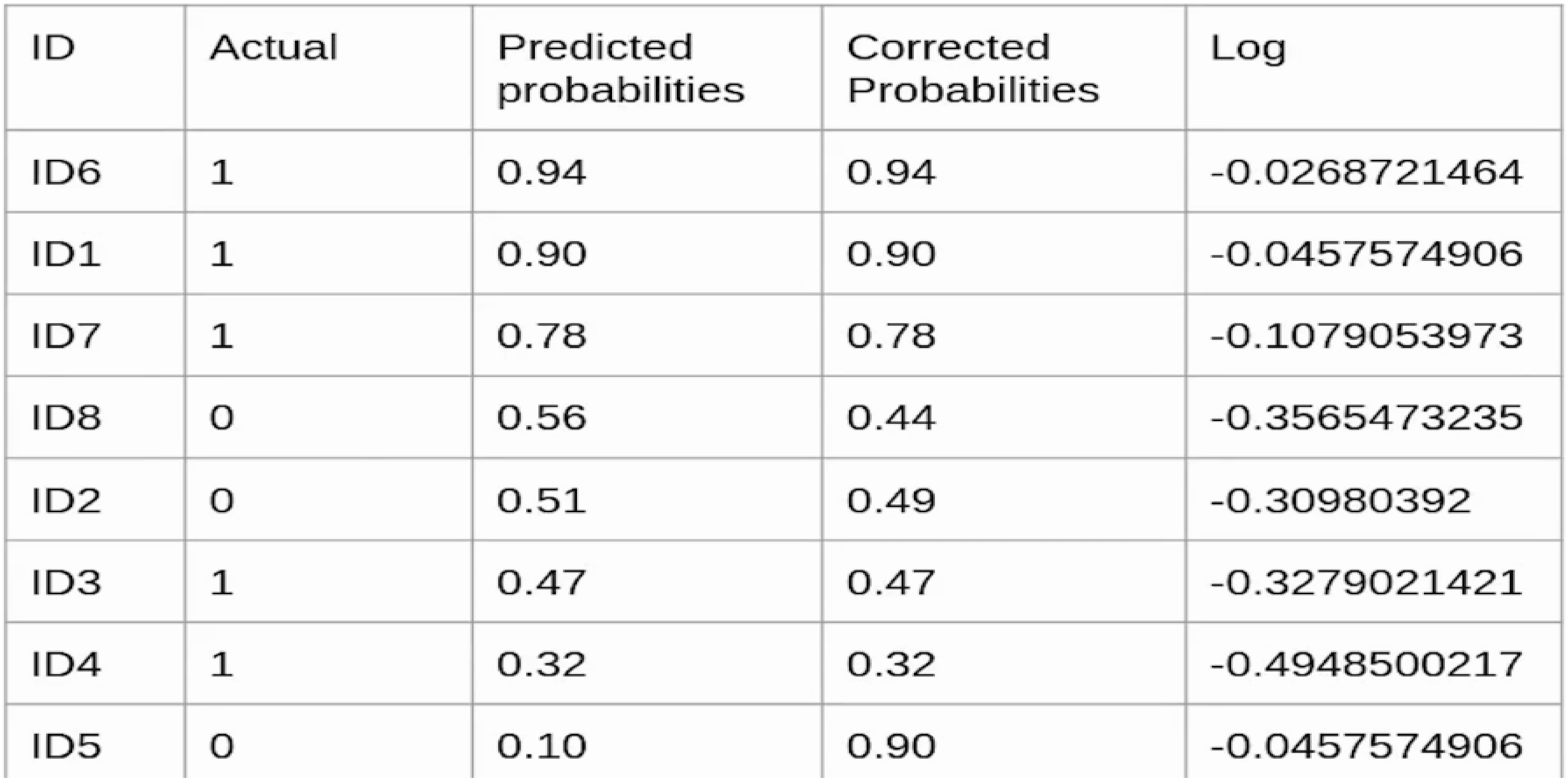


ID	Actual	Predicted probabilities	Corrected Probabilities
ID6	1	0.94	0.94
ID1	1	0.90	0.90
ID7	1	0.78	0.78
ID8	0	**0.56**	**0.44**
ID2	0	**0.51**	**0.49**
ID3	1	0.47	0.47
ID4	1	0.32	0.32
ID5	0	**0.10**	**0.90**

As shown in the above image, ID6 originally belongs to class 1 hence its predicted probability and corrected probability is the same i.e 0.94.

On the other hand, the observation ID8 is from class 0. In this case, the predicted probability i.e. the chances that ID8 belongs to class 1 is 0.56 whereas, the corrected probability means the chances that **ID8 belongs to class 0 is (1- predicted_probability) is 0.44.**

Log(Corrected Probabilities)



ID	Actual	Predicted probabilities	Corrected Probabilities	Log
ID6	1	0.94	0.94	-0.0268721464
ID1	1	0.90	0.90	-0.0457574906
ID7	1	0.78	0.78	-0.1079053973
ID8	0	0.56	0.44	-0.3565473235
ID2	0	0.51	0.49	-0.30980392
ID3	1	0.47	0.47	-0.3279021421
ID4	1	0.32	0.32	-0.4948500217
ID5	0	0.10	0.90	-0.0457574906

We will calculate the log value for each of the corrected probabilities.

The reason behind using the log value is, **the log value offers less penalty for small differences between predicted probability and corrected probability. When the difference is large the penalty will be higher.**

Log(Corrected Probabilities)

We have calculated log values for all the corrected probabilities. Since **all the corrected probabilities lie between 0 and 1, all the log values are negative.** In order **to compensate for this negative value, we will use a negative average of the value**

$$- \frac{1}{N} \sum_{i=1}^{N} (\log(p_i))$$

Further, instead of calculating corrected probabilities, we can calculate the Log loss using the formula given below.

$$\text{Log loss} = \frac{1}{N} \sum_{i=1}^{N} -(y_i * \log(p_i) + (1-y_i) * \log(1-p_i))$$

Here, pi is the probability of class 1, and (1-pi) is the probability of class 0

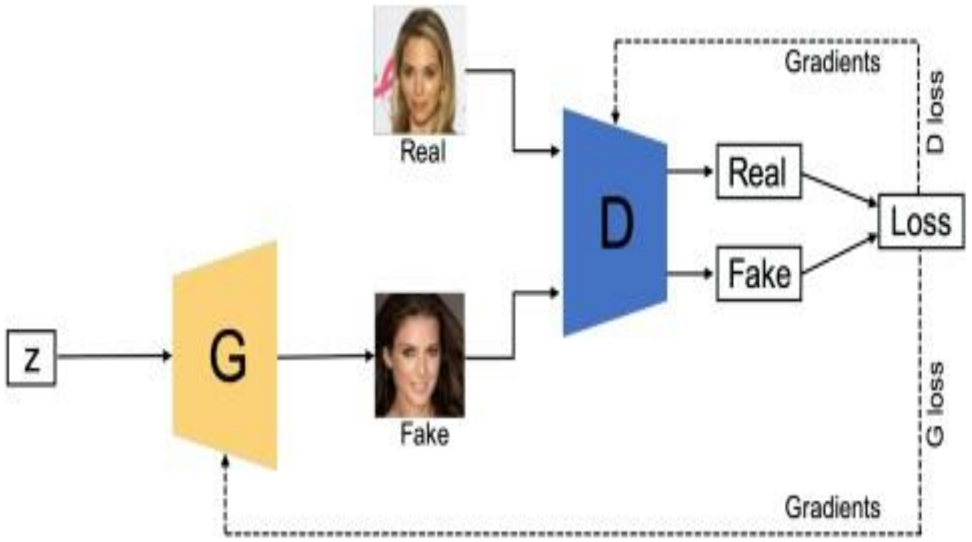
Types of Generative Adversarial Networks (GANs)

The Different Types of Generative Adversarial Networks (GANs) are:

- Vanilla GAN
- Conditional Gan (CGAN)
- Deep Convolutional GAN (DCGAN)
- CycleGAN
- Generative Adversarial Text to Image Synthesis
- Style GAN
- Super Resolution GAN (SRGAN)
- 3D GAN
- SpecGAN
- WaveGAN
- Stack GAN etc.

Vanilla GAN

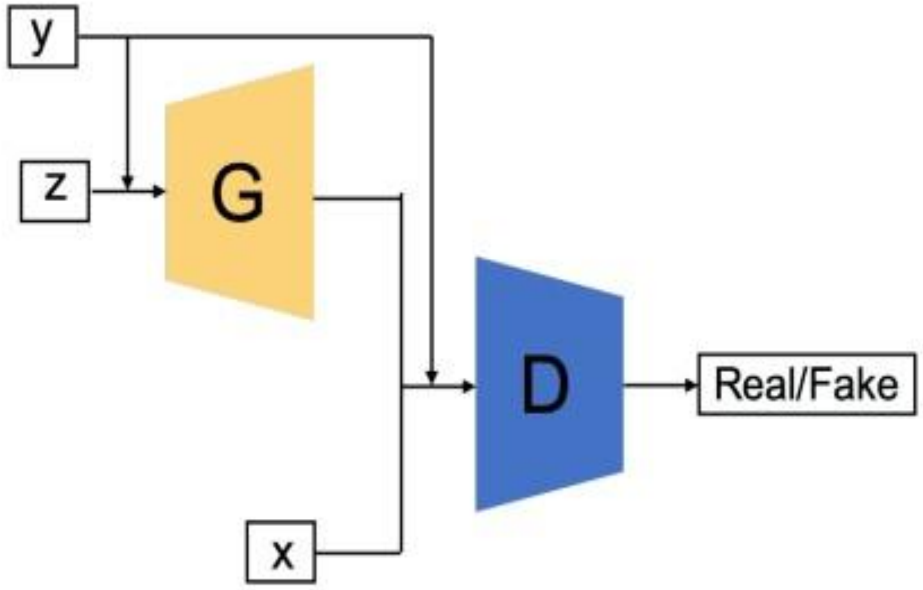
- The **Vanilla GAN is the simplest type of GAN** made up of the generator and discriminator, where the classification and generation of images is done by the generator and discriminator internally **with the use of multi layer perceptrons.**
- The generator captures the data distribution meanwhile, the discriminator tries to find the probability of the input belonging to a certain class.
- Finally, the feedback is sent to both the generator and discriminator after calculating the loss function , and hence the effort to minimize the loss comes into picture.



https://iq.opengenus.org/types-of-gans/

Conditional Gan (cGAN)

- In this GAN, the generator and discriminator both are **provided with additional information that could be a class label or any modal data.**
- As the name suggests the **additional information helps the discriminator in finding the conditional probability instead of the joint probability.**



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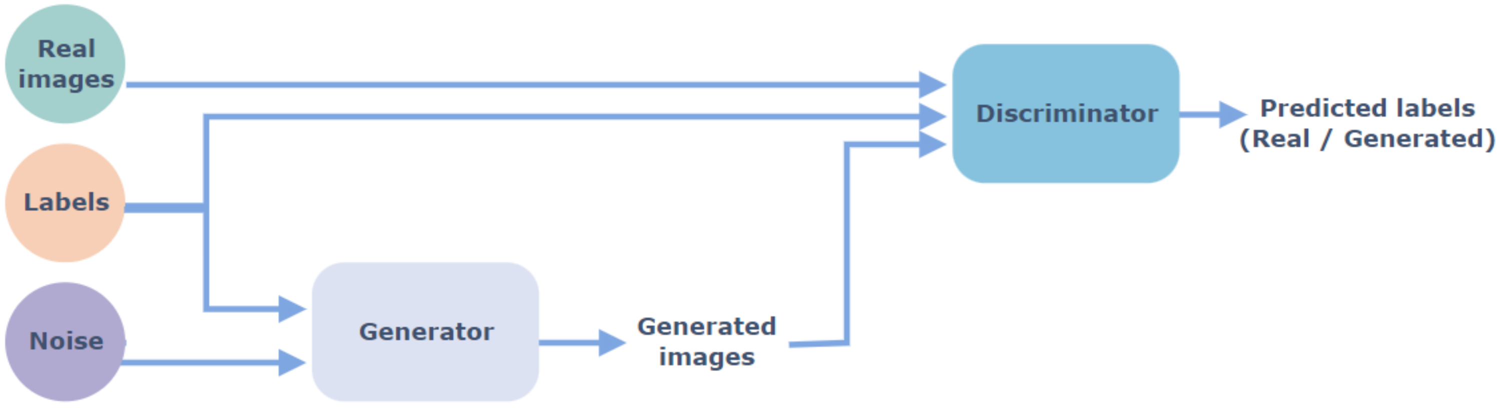
The loss function of the conditional GAN is as below

$$\min_G \max_D \mathbb{E}_{\mathbf{x}\sim p_r} \log[D(\mathbf{x}|\mathbf{y})] + \mathbb{E}_{\mathbf{z}\sim p_\mathbf{z}} \log[1 - D(G(\mathbf{z}|\mathbf{y}))] .$$

Conditional Gan (cGAN)

Suppose you train a GAN on hand-written digits (MNIST images).

- We normally cannot control what specific images the generator will produce.
- In other words, there is no way you can request a particular digit image from the generator.
- This is where the cGANs come in as we can add **an additional input layer of one-hot-encoded image labels.**
- **This additional layer guides the generator in terms of which image to produce.**
- The input to the additional layer can be a feature vector derived either an image that encodes the class or a set of specific characteristics we expect from the image.



Conditional GAN

Conditional Gan (cGAN)-Advantages

- ❑ **By providing additional information, we get two benefits**
  - **Convergence will be faster**. Even the random distribution that the fake images follow will have some pattern.
  - You **can control the output of the generator at test time by giving the label for the image you want to generate.**

- ❑ **Applications**
  - Image-to-image translation
  - Text-to-image synthesis
  - Video generation
  - Convolutional face generation etc.

Deep Convolutional GAN(DCGAN)

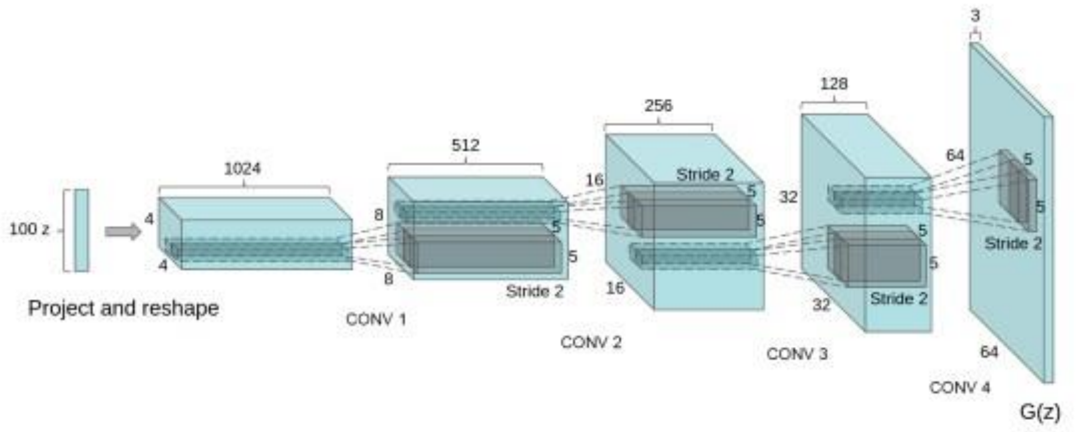
- **Deep Convolutional GAN (DCGAN)** was proposed by a researcher from **MIT and Facebook AI research.**
- It is widely used in many convolution-based generation techniques.
- The focus of this paper was t**o make training GANs stable.**
- Hence, they **proposed some architectural changes.**
- It mainly **composes of convolution layers without max pooling & fully connected layers.**
- It uses **Convolutional Stride and Transposed Convolution for the downsampling and the upsampling.**

Deep Convolutional GAN(DCGAN)

- **DCGAN uses convolutional** and **convolutional-transpose layers in the generator and discriminator**, respectively.
- It was proposed by Radford et. al. in the paper Unsupervised Representation Learning With Deep Convolutional Generative Adversarial Networks.
- The **discriminator consists of strided convolution layers, batch normalization layers, and LeakyRelu as activation function.**
- It takes a **3x64x64 input image**.
- **The generator consists** of **convolutional-transpose layers, batch normalization layers, and ReLU activations.**
- The output will be a 3x64x64 RGB image.
- The **transposed Convolutional Layer** is also known as the **Deconvolutional layer.**
- **Transposed convolution** doesn't reverse the standard convolution by values, rather by dimensions only.

Deep Convolutional GAN (DCGAN)

- This is the **First GAN where the generator used deep convolutional network** , hence generating high resolution and quality images to be differentiated.
- **ReLU activation** is used in Generator all layers except last one where **Tanh** activation is used, meanwhile **in Discriminator** all layers uses the **Leaky-ReLu activation function.**
- **Adam optimizer** is used to update network weights iterative based in training data with a Learning Rate of 0.0002.



https://iq.opengenus.org/types-of-gans/

The above figure shows the architecture of generator of the GAN. The input generated is of 64 X 64 resolution.

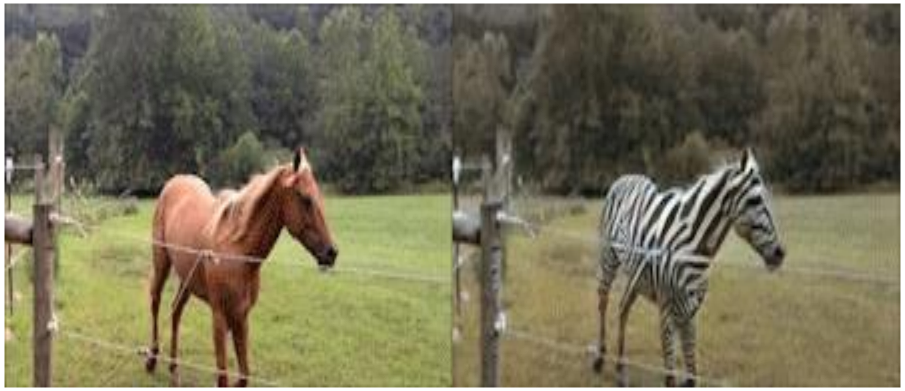
Need for DCGANs:

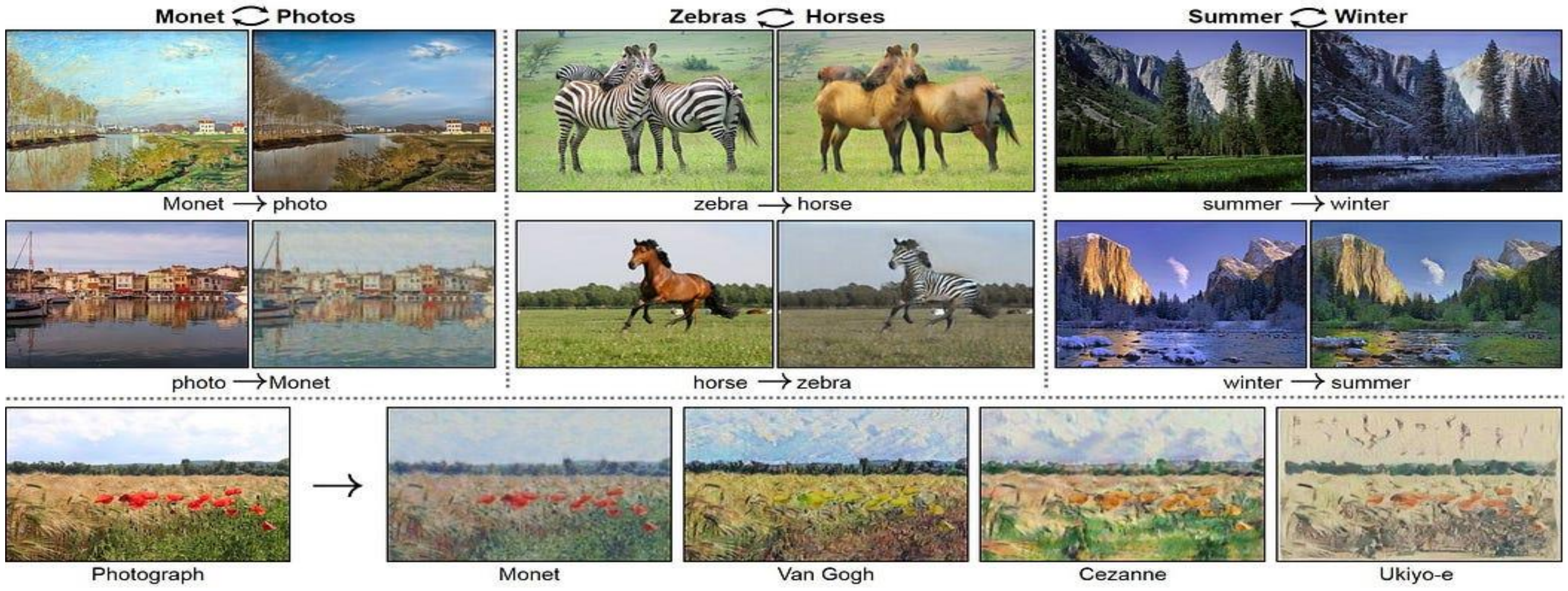
- **DCGANs are introduced to reduce the problem of mode collapse.**
- Mode collapse occurs when **the generator got biased towards a few outputs and can’t able to produce outputs of every variation from the dataset.**
- For example- take the case of mnist digits dataset (digits from 0 to 9) , we want the generator should generate all type of digits but sometimes our generator got biased towards two to three digits and produce them only.
- Because of that the discriminator also got optimized towards that particular digits only, and **this state is known as Mode Collapse.**
- But this problem can be overcome by using DCGANs.

CycleGAN

- **This GAN is made for Image-to-Image Translations**, meaning one image to be mapped with another image.

A mapping function
Is used to convert
Image into image





https://medium.com/coding-blocks/introduction-to-cyclegans-1dbdb8fbe781

CycleGAN-Architecture

CycleGAN is a Generative Adversarial Network (GAN) that **uses *two* generators and *two* discriminators.**

We call one generator G, and it converts images from the X domain to the Y domain. The other generator is called F, and converts images from Y to X.

$$G : X \longrightarrow Y$$

$$F : Y \longrightarrow X$$

Both G and F are generators that take an image from one domain and translate it to another. G maps from X to Y, whereas F goes in the opposite direction, mapping Y to X.

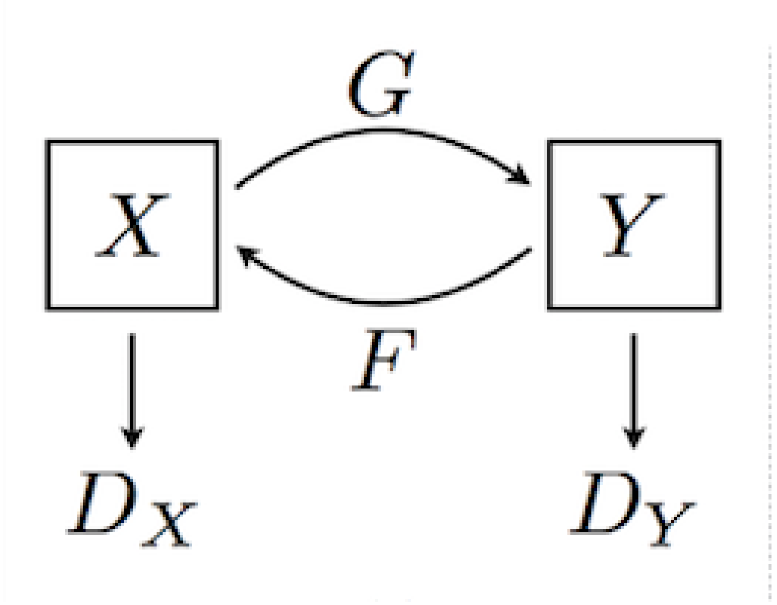
Each generator has a corresponding discriminator, which attempts to tell apart its synthesized images from real ones.

Dy: Distinguishes y from G(x)

Dx: Distinguishes x from F(y)

One discriminator provides adversarial training for G, and the other does the same for F.

CycleGAN-Architecture


$$\begin{tikzcd} X \arrow[r, bend left, "G"] \arrow[d] & Y \arrow[l, bend left, "F"] \arrow[d] \\ D_X & D_Y \end{tikzcd}$$

It consists of :

•Two mappings ***G : X -> Y*** and ***F : Y -> X***

•Corresponding Adversarial discriminators **Dx** and **Dy**

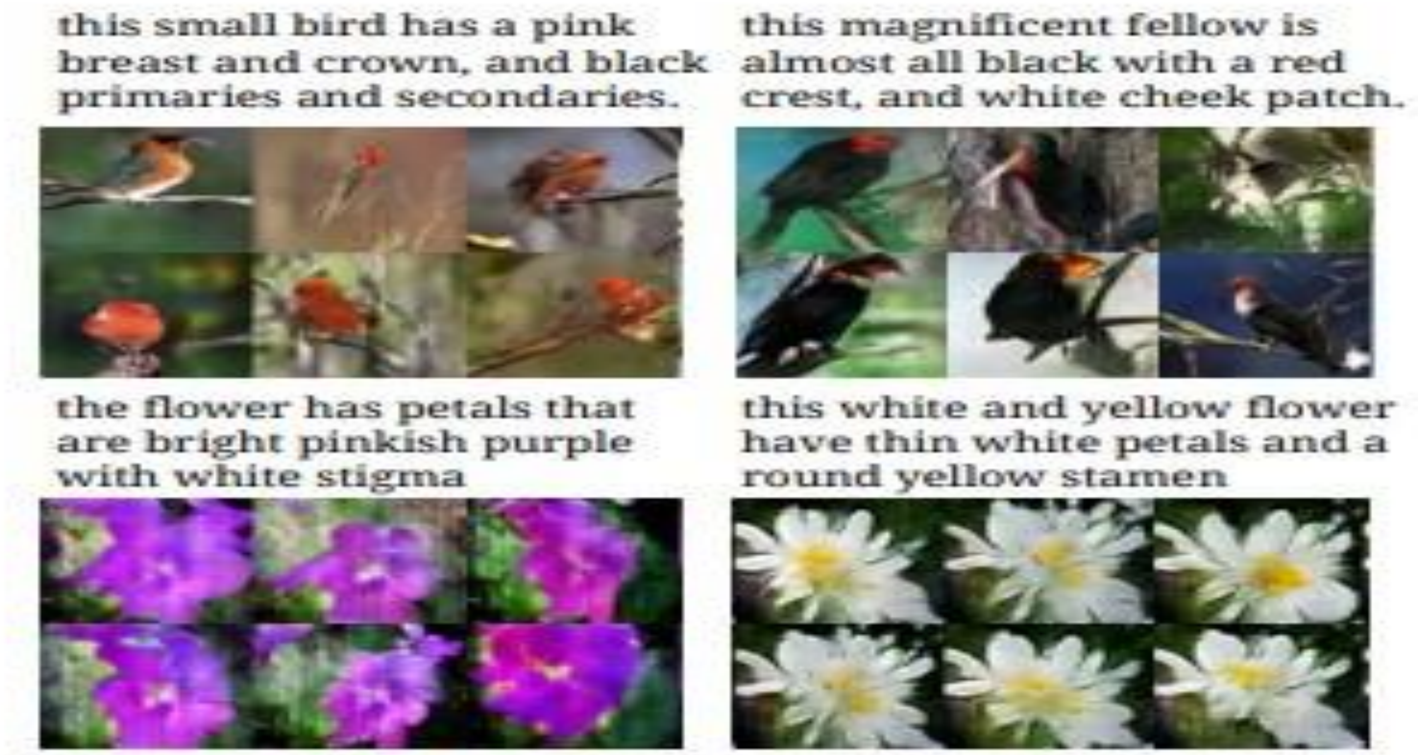
Role of G: G is trying to **translate** X into outputs, which are fed through Dy to check whether they are real or fake according to Domain Y

Role of F : F is trying to **translate** Y into outputs, which are fed through Dx to check if they are indistinguishable from Domain X

https://medium.com/coding-blocks/introduction-to-cyclegans-1dbdb8fbe781

Generative Adversarial Text to Image Synthesis

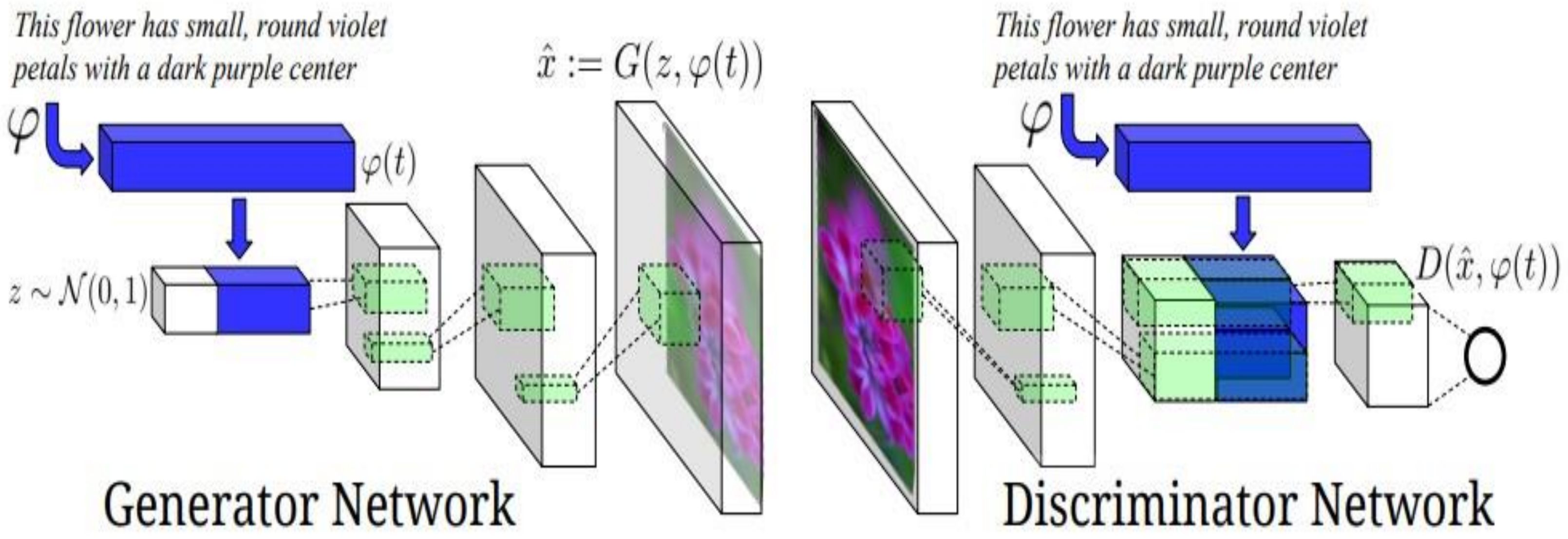
- In this the GANs are capable of finding an image from the dataset that is closest to the text description and generate similar images.


this small bird has a pink breast and crown, and black primaries and secondaries.
this magnificent fellow is almost all black with a red crest, and white cheek patch.
the flower has petals that are bright pinkish purple with white stigma
this white and yellow flower have thin white petals and a round yellow stamen

https://iq.opengenus.org/types-of-gans/

The GAN architecture in this case is given below:

- As, the generator network generates based on the description and the differentiation is done by the discriminator based on the features mentioned in text description.

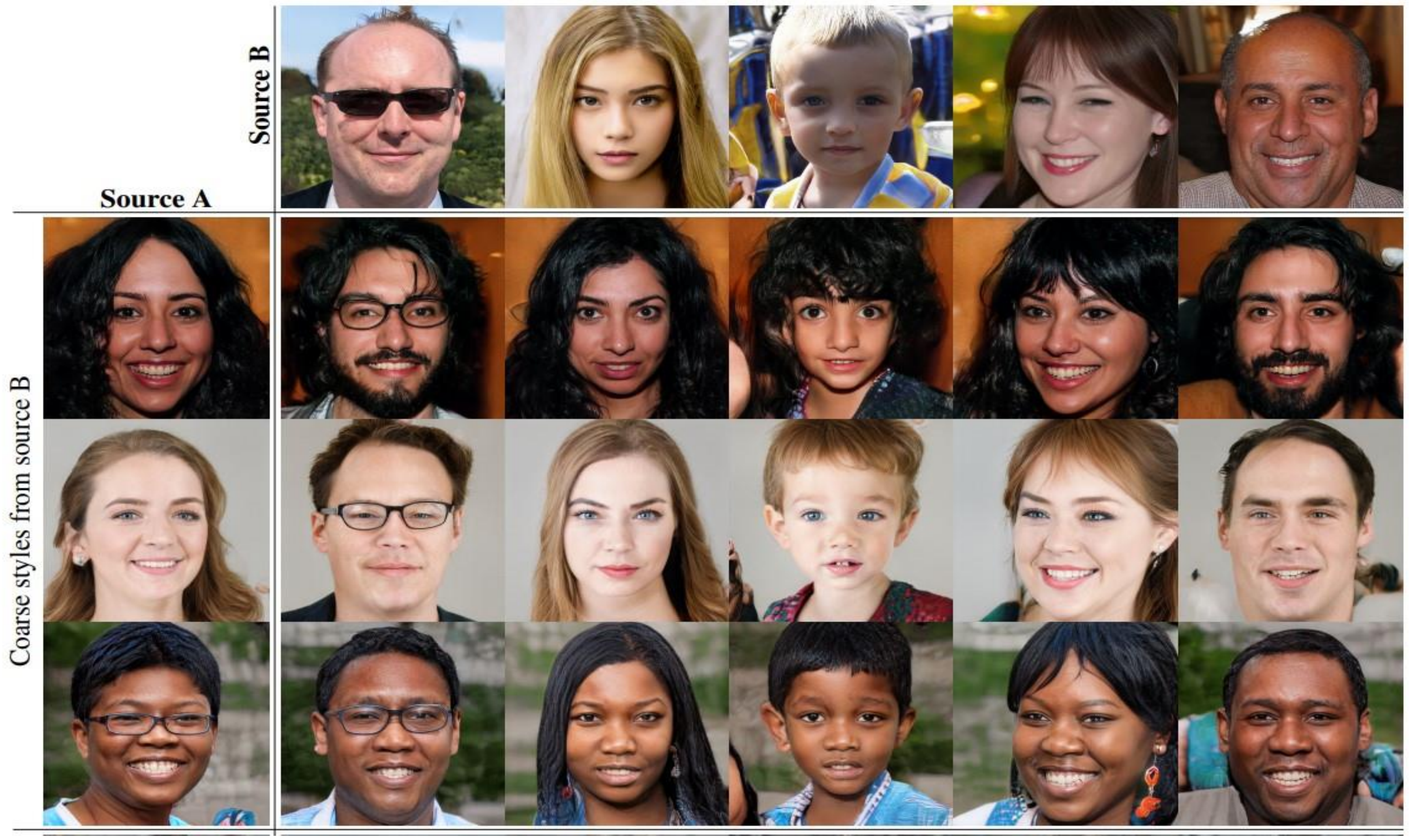

This flower has small, round violet petals with a dark purple center
φ
$\varphi(t)$
$z \sim \mathcal{N}(0,1)$
$\hat{x} := G(z, \varphi(t))$
This flower has small, round violet petals with a dark purple center
φ
$D(\hat{x}, \varphi(t))$
Generator Network
Discriminator Network

https://iq.opengenus.org/types-of-gans/

A deep convolutional generative adversarial net- work (DC-GAN) conditioned on text features.

Style GAN

- Other GANs focused on improving the discriminator in this case we improve the generator. **This GAN generates by taking a reference picture.**



https://iq.opengenus.org/types-of-gans/

Style GAN

❑ **There are three main Components of StyleGAN**

1. Progressive Growing,
2. Noise Mapping Network,
3. Adaptive Instance Normalization.

https://iq.opengenus.org/types-of-gans/

Style GAN

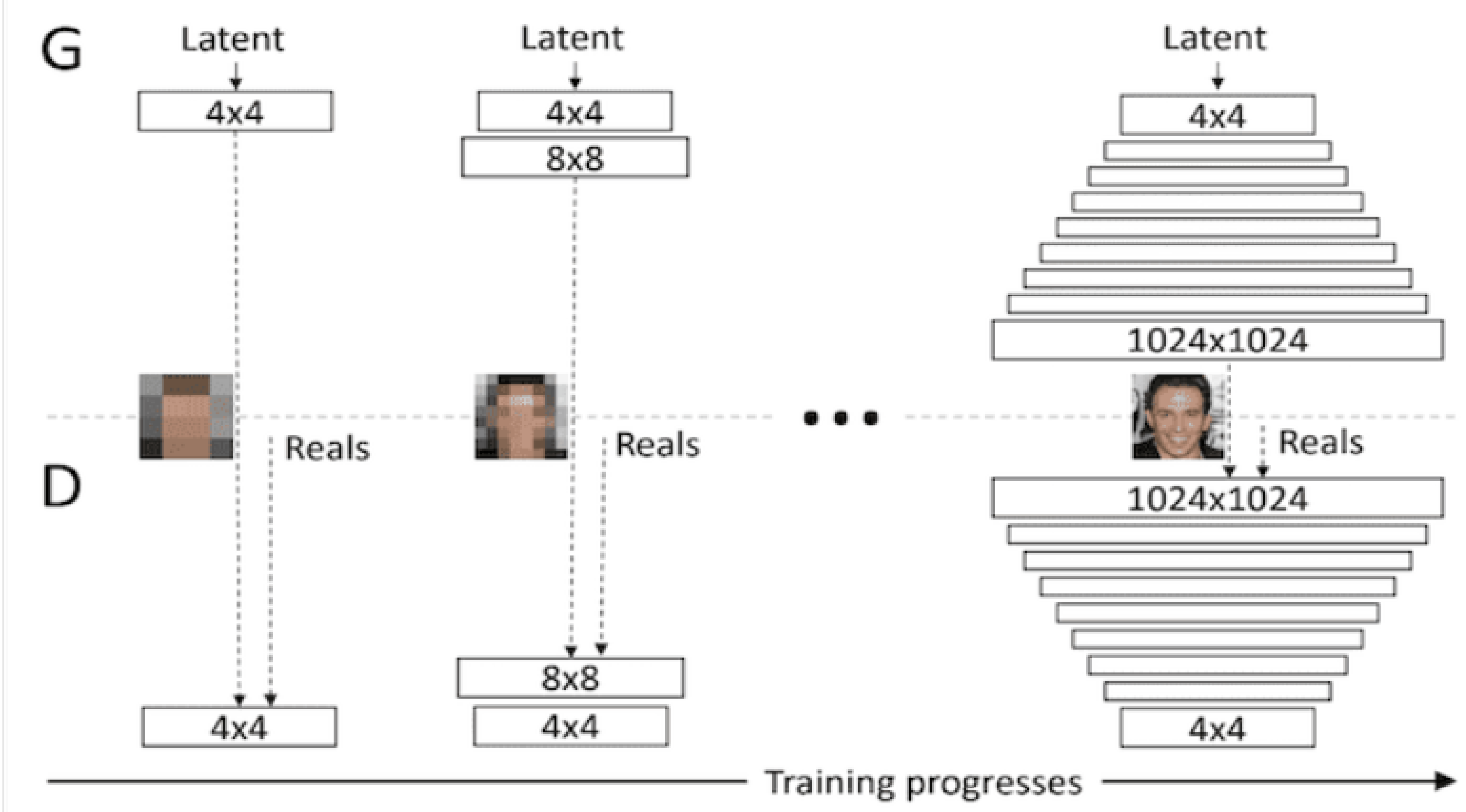
1. Progressive Growing

- This means that both models start with small images, in this case, 4×4 images. The models are fit until stable, then both discriminator and generator are expanded to double the width and height (quadruple the area), e.g. 8×8.
- A new block is added to each model to support the larger image size, which is faded in slowly over training.
- Once faded-in, the models are again trained until the desired target image size is met, such as 1024×1024.
- The progressive growing GAN **uses nearest neighbor layers for upsampling instead of transpose convolutional layers** that are common in other generator models.

https://iq.opengenus.org/types-of-gans/

Style GAN

1. Progressive Growing



Example of Progressively Adding Layers to Generator and Discriminator Models.
Taken from: Progressive Growing of GANs for Improved Quality, Stability, and Variation.

https://iq.opengenus.org/types-of-gans/

Style GAN

2. Mapping Network and AdaIN

- A standalone mapping network is used that takes a randomly sampled point from the latent space as input and generates a style vector. (Latent space is a simpler, hidden representation of a data point.)
- The mapping network is comprised of eight fully connected layers, e.g. it is a standard deep neural network.
- The style vector is then transformed and incorporated into each block of the generator model after the convolutional layers via an operation called adaptive instance normalization or AdaIN.
- The **AdaIN layers** involve first standardizing the output of feature map to a standard Gaussian, then adding the style vector as a bias term.

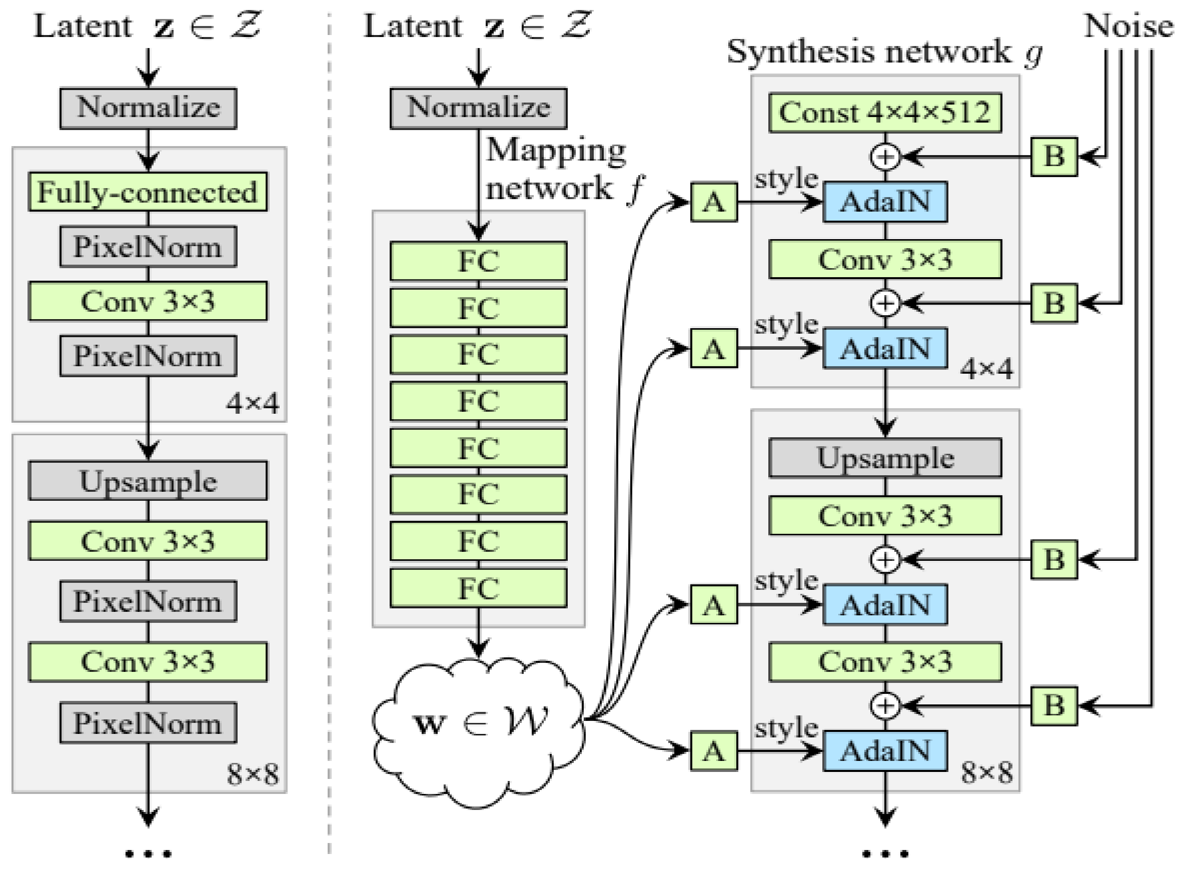
https://iq.opengenus.org/types-of-gans/

Style GAN

- StyleGAN produces the **simulated image sequentially**, originating from a simple resolution and **enlarging to a huge resolution (1024×1024). (Progressive Growing GANs)**
- By transforming the input of each level individually, it examines the **visual features that are manifested in that level, from standard features (pose, face shape) to minute details (hair color),** without altering other levels.
- The resulting model is proficient in producing **impressively photorealistic high-quality photos of faces.**
- It **grants control** over **the characteristic of the created image** at **different specification levels by changing the style vectors and noise.**
- **The noise is** affixed to whole feature maps that **enable the model to understand the style in a fine-grained, per-pixel manner.**

Style GAN

- As you an see the figure below, Style Gan architecture consists of a Mapping network that maps the input to an intermediate Latent space.
- Further the intermediate is processed using the AdaIN after each layer , there are approximately 18 convolutional layers.



(a) Traditional (b) Style-based generator

https://www.analyticsvidhya.com/blog/2021/05/stylegan-explained-in-less-than-five-minutes/

Style GAN

- The Style GAN uses the AdaIN or the Adaptive Instance Normalization which is defined as

$$\mathrm{AdaIN}(\mathbf{x}_i, \mathbf{y}) = \mathbf{y}_{s,i} \frac{\mathbf{x}_i - \mu(\mathbf{x}_i)}{\sigma(\mathbf{x}_i)} + \mathbf{y}_{b,i},$$

Here, x_i is the feature map , which is tweaked by using the component y.

- **A separate convolutional layer's input** is **normalized** with **adaptive instance normalization (AdaIN) operation** using the latent vector **"style" embeddings.**
- Lastly, added noise is included in the network to generate more stochastic details in the images.
- This noise is just a single-channel picture consisting of uncorrelated Gaussian noise.
- Before each AdaIN operation, noise is supplied at a specific convolutional layer.
- Additionally, there is a scaling part for the noise, which is decided per feature.

Example

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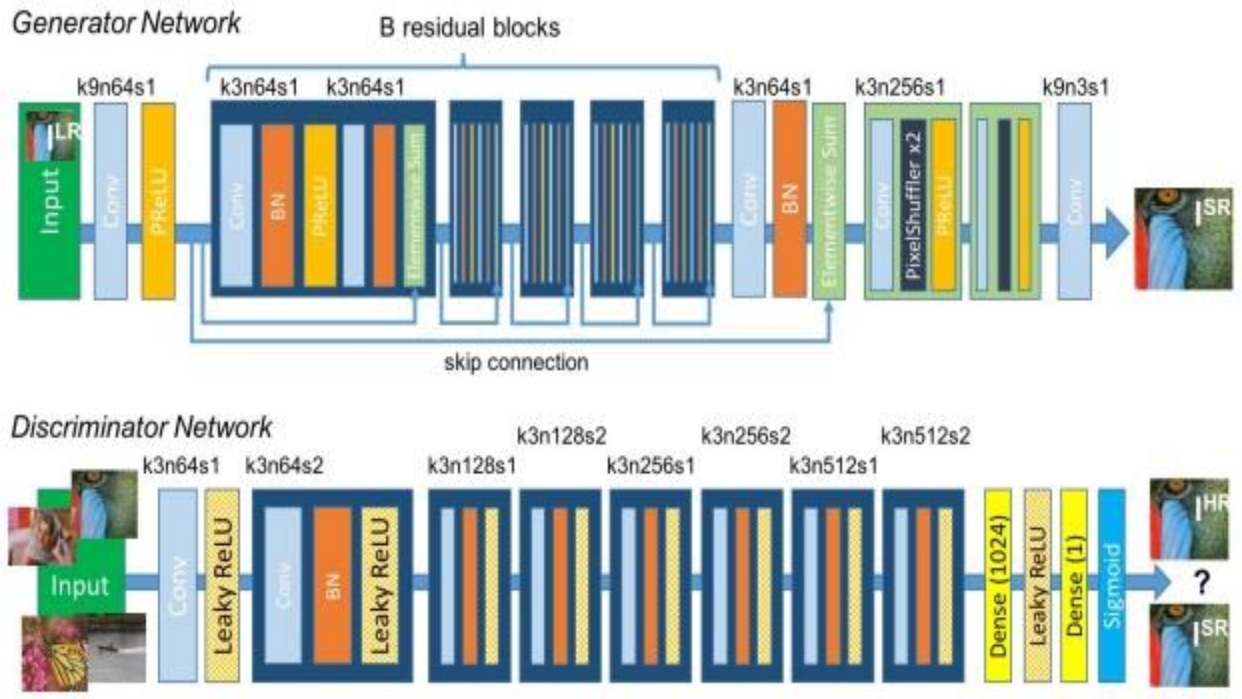
Super Resolution GAN (SRGAN)

- The main purpose of this type of GAN is to make a low-resolution picture into a more detailed picture.
- This is one of the most researched problems in Computer vision. The architecture of the SRGAN is given below



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Super Resolution GAN (SRGAN)

- As given in the above figure we observe that the Generator network and Discriminator both make use of Convolutional layers, the Generator make use of the Parametric ReLU as the activation function whereas the Discriminator uses the Leaky ReLU.
- The Generator takes the input data and finds the average of all possible solutions that is pixelwise, when formulated looks like,

$$\hat{\theta}_G = \arg\min_{\theta_G} \frac{1}{N} \sum_{n=1}^{N} l^{SR}(G_{\theta_G}(I_n^{LR}), I_n^{HR})$$

here, I^{HR} represents high resolution image , whereas I^{LR} represents lower resolution image and l^{SR} represents loss and θ_g represents the weight and biases at layer L. Now the perceptual loss is given as

https://iq.opengenus.org/types-of-gans/

Super Resolution GAN (SRGAN)

$$l^{SR} = \underbrace{\underbrace{l^{SR}_{X}}_{\text{content loss}} + \underbrace{10^{-3} l^{SR}_{Gen}}_{\text{adversarial loss}}}_{\text{perceptual loss (for VGG based content losses)}}$$

Finally, the content loss is summed with adversial loss and Mean Squared Error is taken to find the best pixel wise solution.

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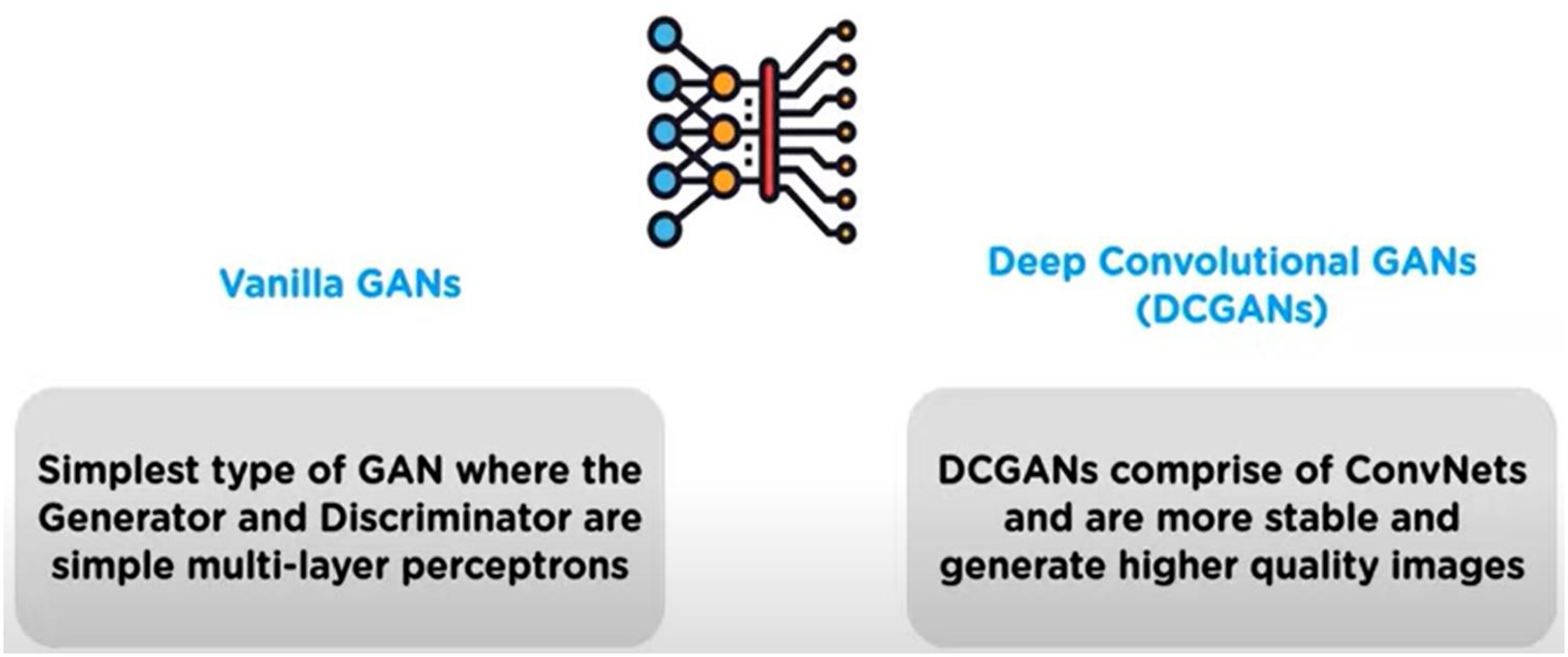
Vanilla GANs & DCGANs



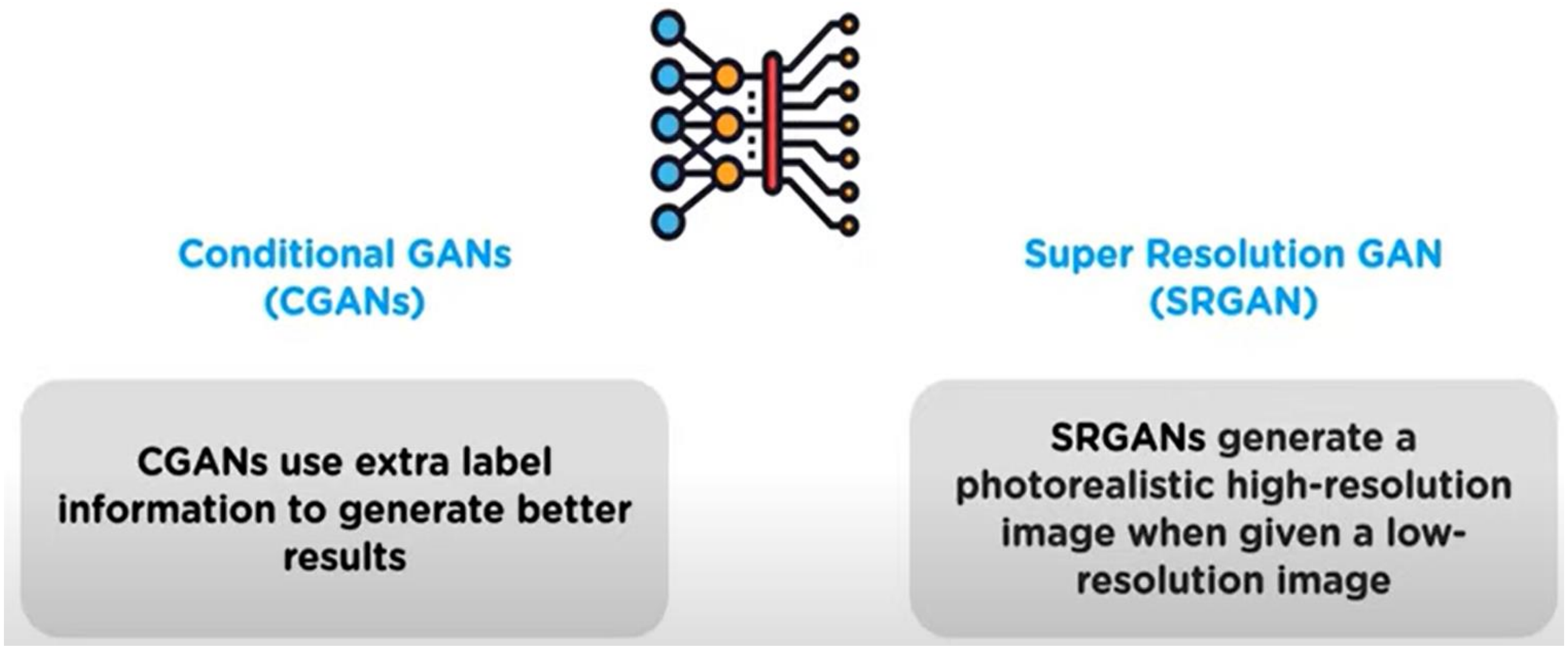
Vanilla GANs

Deep Convolutional GANs (DCGANs)

Simplest type of GAN where the Generator and Discriminator are simple multi-layer perceptrons

DCGANs comprise of ConvNets and are more stable and generate higher quality images

CGANs & SRGANs



Conditional GANs (CGANs)

CGANs use extra label information to generate better results

Super Resolution GAN (SRGAN)

SRGANs generate a photorealistic high-resolution image when given a low-resolution image

Applications of GANs

1.Firstly, **GANs can be used as data augmentation techniques** where the generator generates new images taking the training dataset and producing multiple images by applying some changes.

2.GANs improve the classification techniques by training the discriminator on a very large scale of data that are real as well as fake.

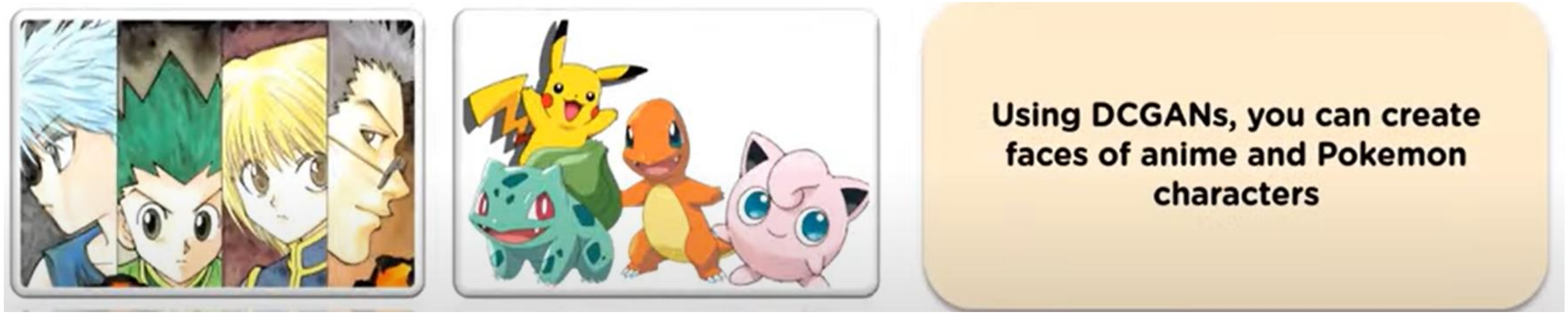
3.GANs are also used to improve the resolution of any input image.

4.Just **like filters used in Snapchat**, a filter could be applied to see what a place might look like if **in summer, winter, spring or autumn and many more conditions** could be applied.

5.GANs are used to convert semantics into images and better understand the visualizations done by the machine etc.

Applications of GANs

1. Generating Cartoon Characters


Using DCGANs, you can create faces of anime and Pokemon characters

Applications of GANs

2. Generating Human Faces

GANs can be trained on the images of humans to generate realistic faces

Applications of GANs

3. Text to Image Translation

Bird with a black head, yellow body and a short beak →

GANs can build realistic images from textual descriptions of simple objects like birds

A Flower With Red Petals And Green Leaves

Applications of GANs

4. 3-D object Generation-3-D GAN

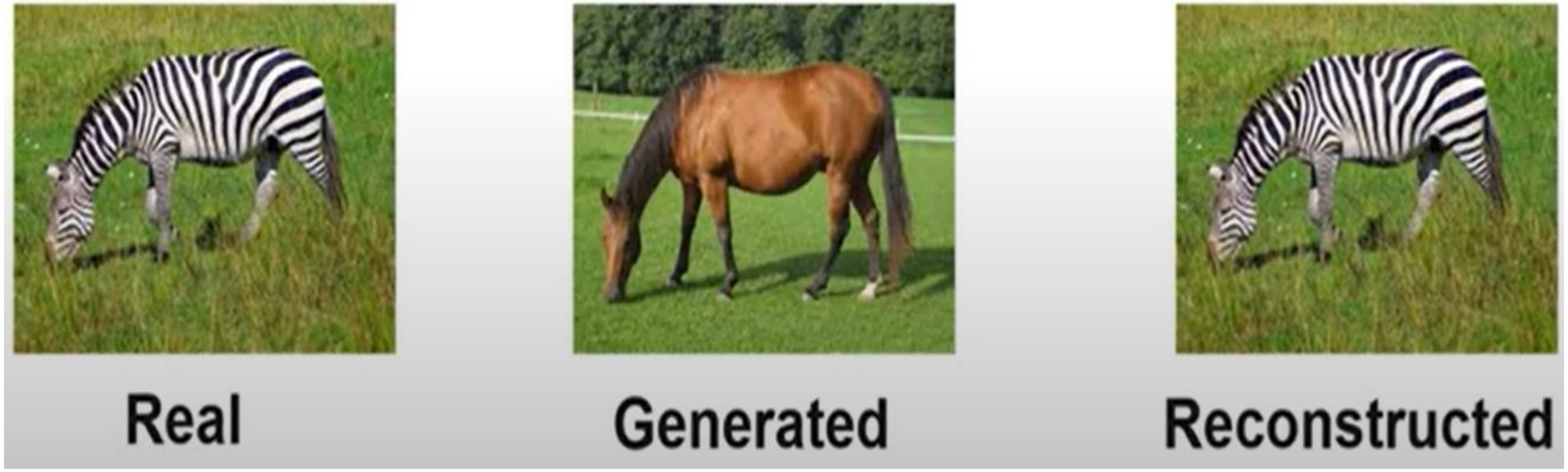
GANs can generate 3-D models using 2-D pictures of objects from multiple perspectives

Applications of GANs

5. Prediction of Next Frame in A Video

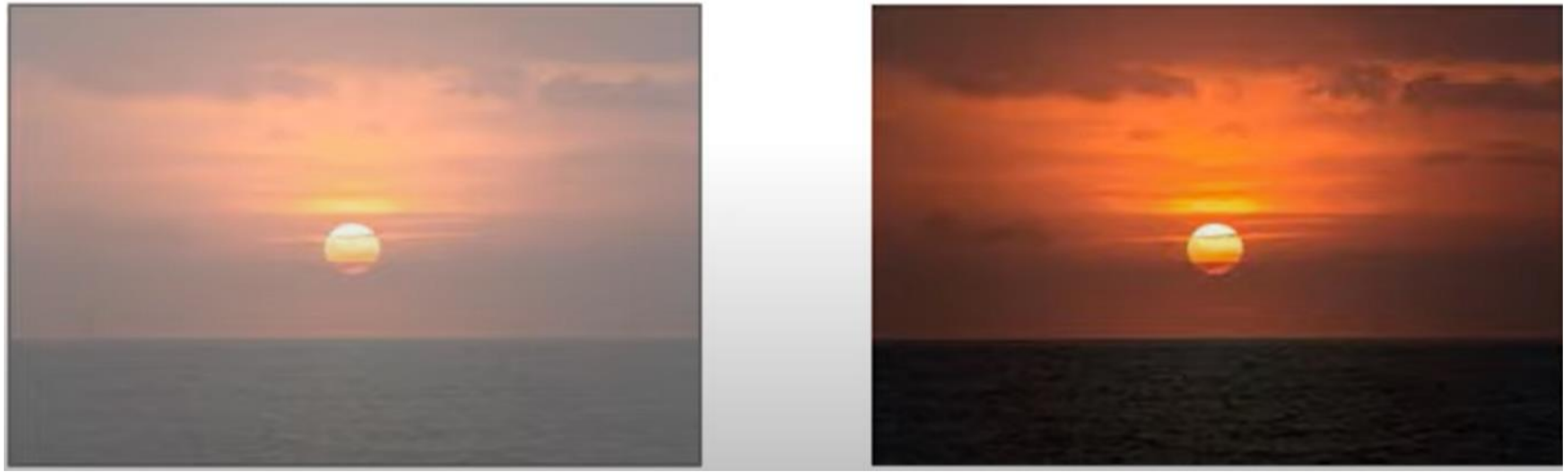
Applications of GANs

6. Image to Image Translation-Cycle GAN



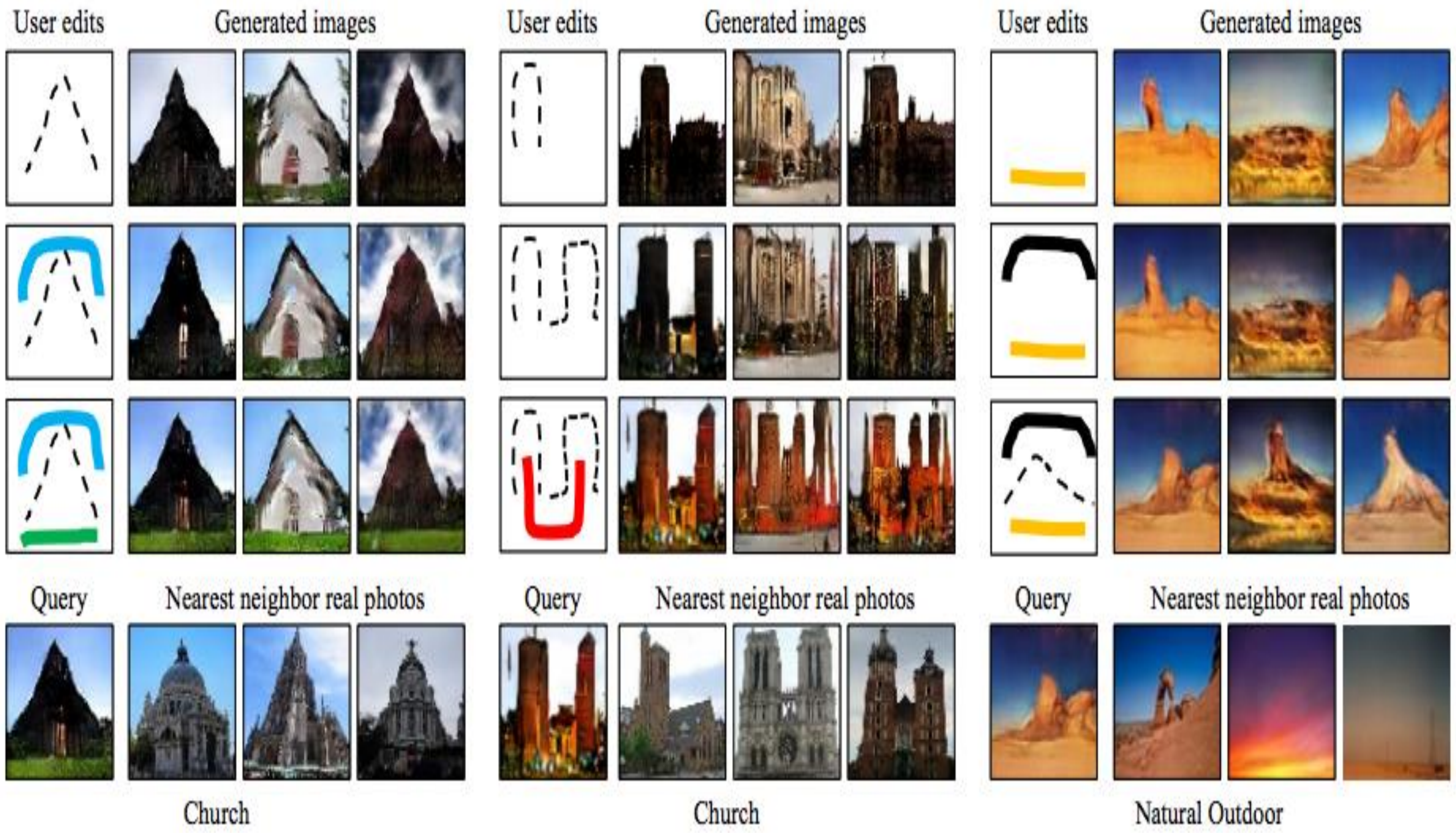
Applications of GANs

7. Enhancing the Resolution of an Image using Super Resolution GANs

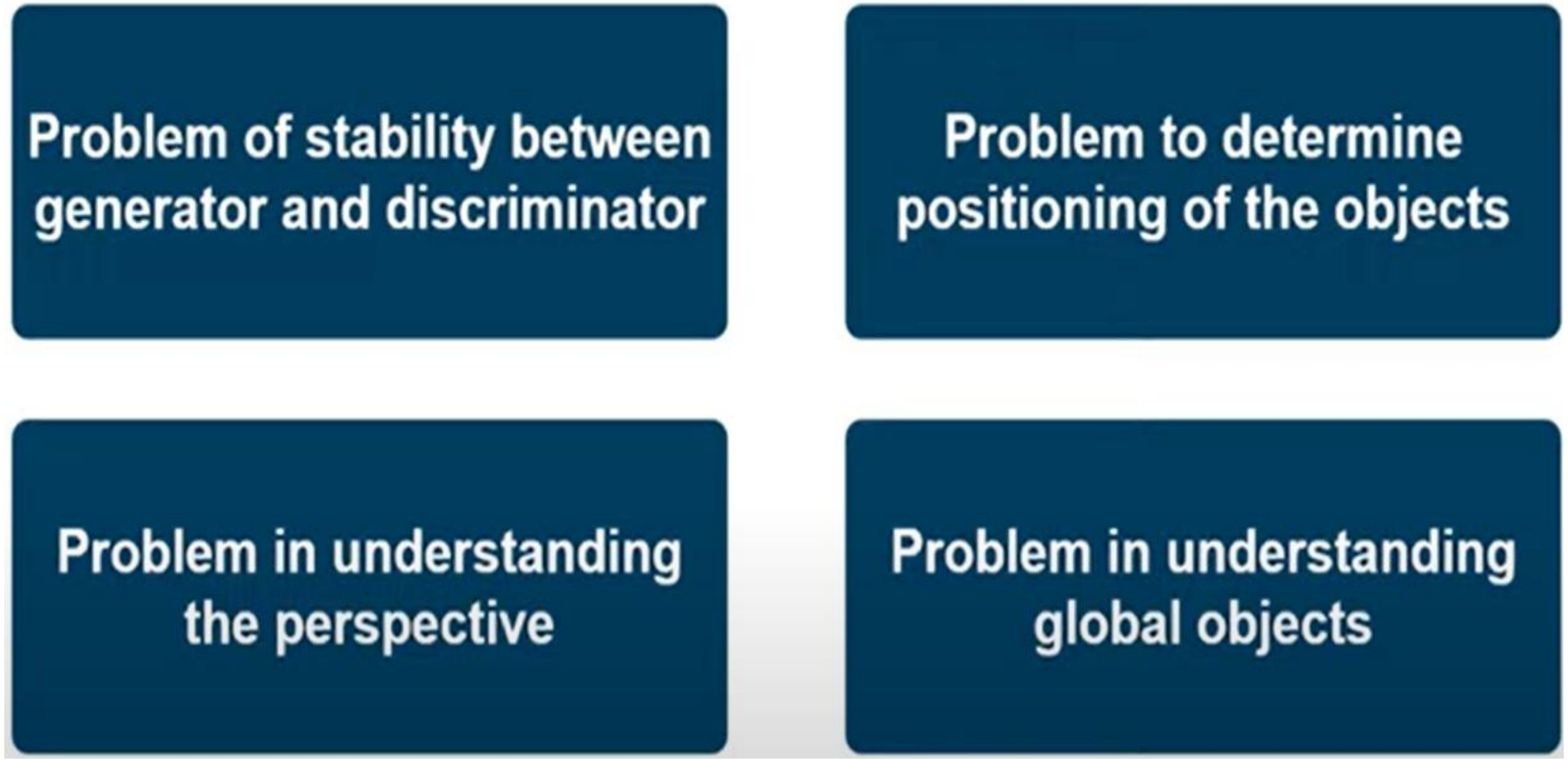


Applications of GANs

8. Interactive Image Generation



Challenges Faced by GANs



Problem of stability between generator and discriminator

Problem to determine positioning of the objects

Problem in understanding the perspective

Problem in understanding global objects

Deep Convolutional GAN and recent GANs are more advanced. We can overcome problems using it

Diolch
Kiitos
Sheun
umesc
Kasih
Todah
Shnorhakalutiun
Mamnoon
Shokriya
Dziękuję
Shokrun
Spaas
Mul
Ači
Gamsahapnida
Teşekkür
Dekuju/Dekujeme
Hvala
Ngiyabonga
Xie
Dank
Takk
Cam
Gra
or
Dhanyavaad
Dakujem
Waad
Dhanyavaadalu
Kop
Salamat
Merci
al
Dankie
Go
Grazie
Faleminderit
Daw
Dhanyavad
Khopjai
Kruthagnathalu
krap
Thank You
kun
Arigatou
Tack
Or
Dhonnobaad
Shukriya
ederim
Asante
Grazzi
raibh
Gracias
Nandree
Blagodariya
Gomapsupnida
Euxaristo
Kun
Hain
Dhan
Fyrir
Terima
Enkosi
Danke
dank
daa