

An abstract graphic on the left side of the slide, featuring a dark blue background with a complex network of glowing white and light blue lines and nodes, resembling a neural network or a data structure.

# Generative Adversarial Networks

Shobhit

Software Engineer, Qualcomm

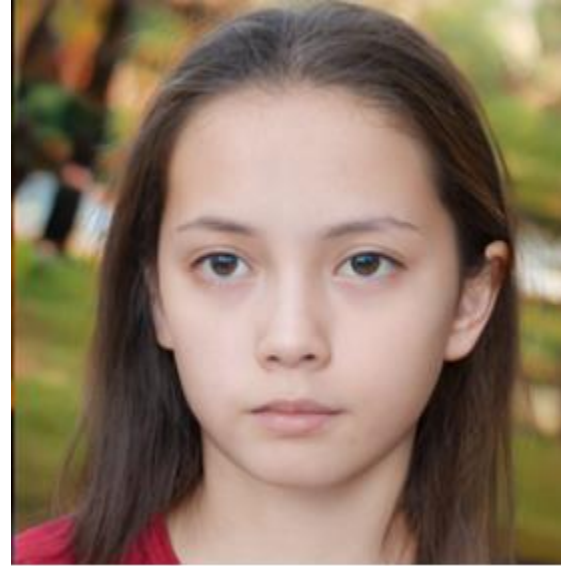
IIT Bhubaneswar, India

An abstract graphic on the left side of the slide, featuring a dark blue background with a complex network of glowing blue lines and nodes, resembling a neural network or a data visualization.

# Agenda

- Game
- Generative modelling
- Coolest applications
- GANs components and its architecture
- GANs training
- Difficulties during training
- Use case

# Let's Play Game - Identify Real or Fake One

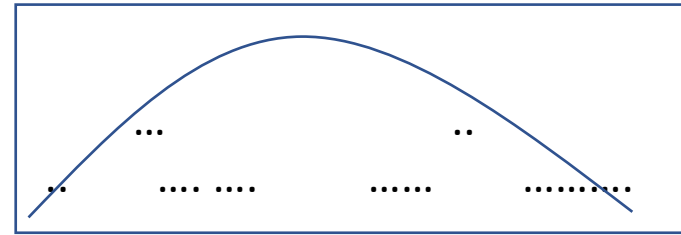


Generated From StyleGAN2



**These People Don't Exist**

# Generative Modelling – Density Estimation





# Generative Modelling – Sample Generation



**Celeb A dataset**



**Generated Images**

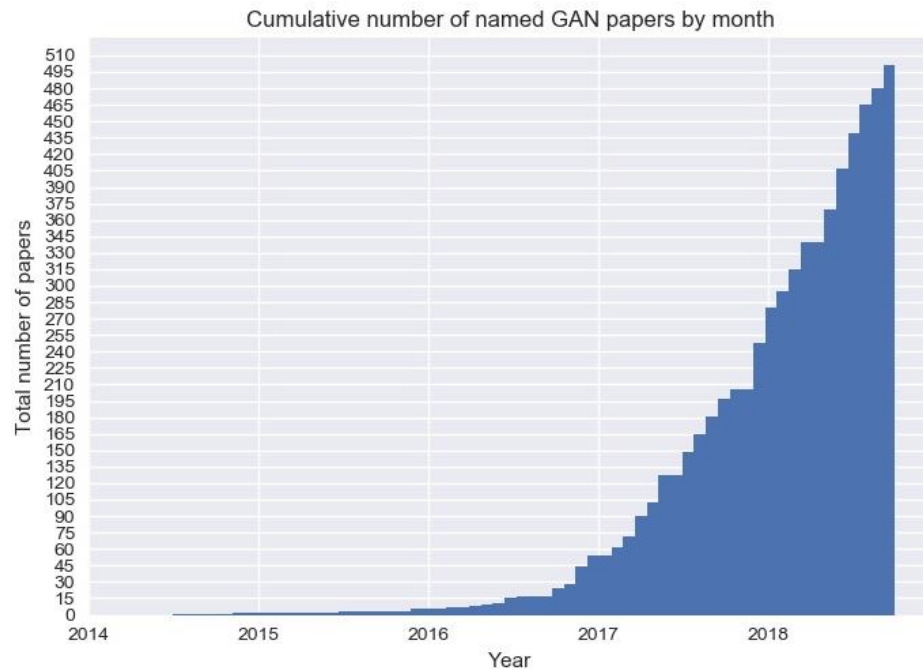
Tero Karras et.al. (2018). Progressive Growing of GANs for Improved Quality, Stability, and Variation.

# Inventor of GANs – Ian Goodfellow



Ian Goodfellow @goodfellow\_ian · Jan 15, 2019

4.5 years of GAN progress on face generation. [arxiv.org/abs/1406.2661](https://arxiv.org/abs/1406.2661)  
[arxiv.org/abs/1511.06434](https://arxiv.org/abs/1511.06434) [arxiv.org/abs/1606.07536](https://arxiv.org/abs/1606.07536)  
[arxiv.org/abs/1710.10196](https://arxiv.org/abs/1710.10196) [arxiv.org/abs/1812.04948](https://arxiv.org/abs/1812.04948)



<https://github.com/hindupuravinash/the-gan-zoo>



Ian Goodfellow @goodfellow\_ian · Jul 12, 2019

I'm in Fortune's 40 under 40:



Ian Goodfellow

Industry: A.I. As one of the youngest and most respected A.I. researchers in the world, Ian Goodfellow has kept busy pushing the frontiers of de...

[fortune.com](https://fortune.com)

Around 33,300 citation is on original paper of GANs



Google Scholar

Generative Adversarial Networks

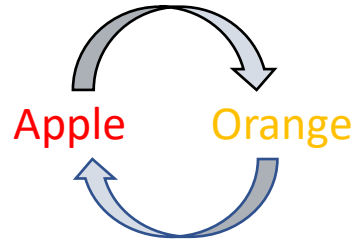


Articles

About 90,700 results (0.04 sec)



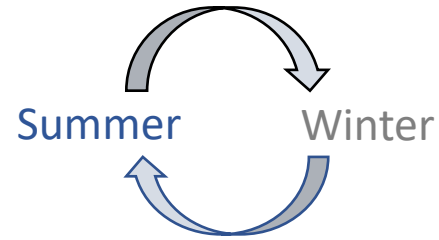
# Coollest Application – CycleGAN



Apple → Orange



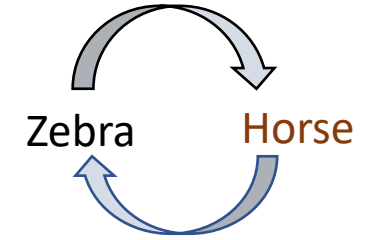
Orange → Apple



Summer → Winter



Winter → Summer



Zebra → Horse

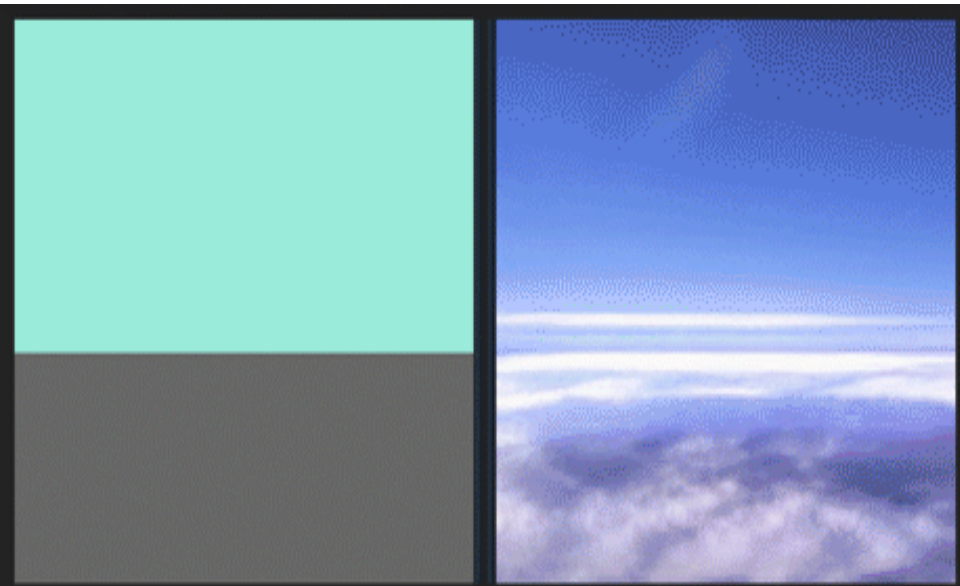


Horse → Zebra

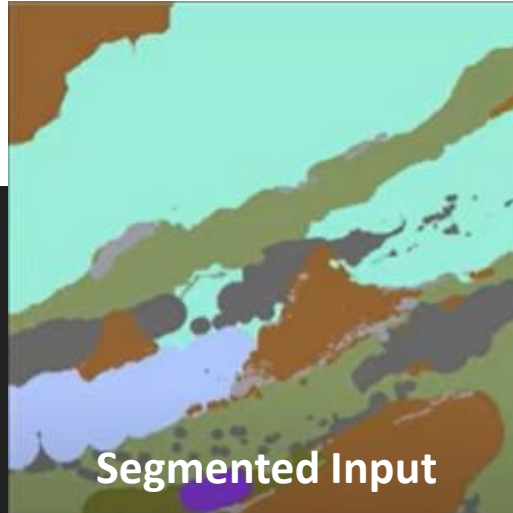
Zhu, Jun-Yan, et al(2020). 'Unpaired Image-to-Image Translation Using Cycle-Consistent Adversarial Networks'.

(Shobhit)

# Coollest Application – Nvidia GauGAN



<http://nvidia-research-mingyuliu.com/gaugan/>



Segmented Input



GauGAN Output



Colie Wertz Paint Over

Colie Wertz, Senior Concept Artist [Rogue one: A Starwars story](#), [Bumblebee](#), [Captain America: Civil Wars](#)

(Shobhit)



# Coollest Application

Living portraits



Zakharov, Egor, et al.(2019) “Few-shot adversarial learning of realistic neural talking head models”

# Companies Using GANs



# Why GANs

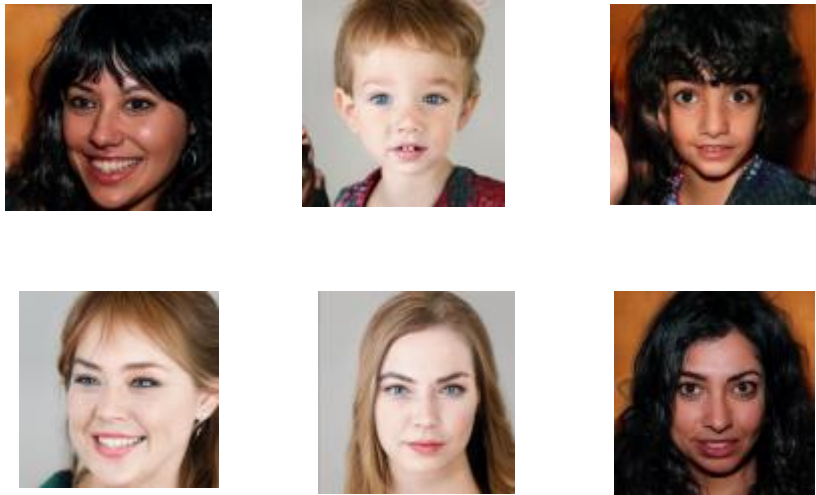
- Simulate all possible future plans
- Missing Values
- Realistic generation tasks
- Avoids Multi-modal outputs
- Data Augmentations



# GANs Components

## Generator

It will generate **Fakes data** that looks like **Real**  
It is like a **Art Forger**

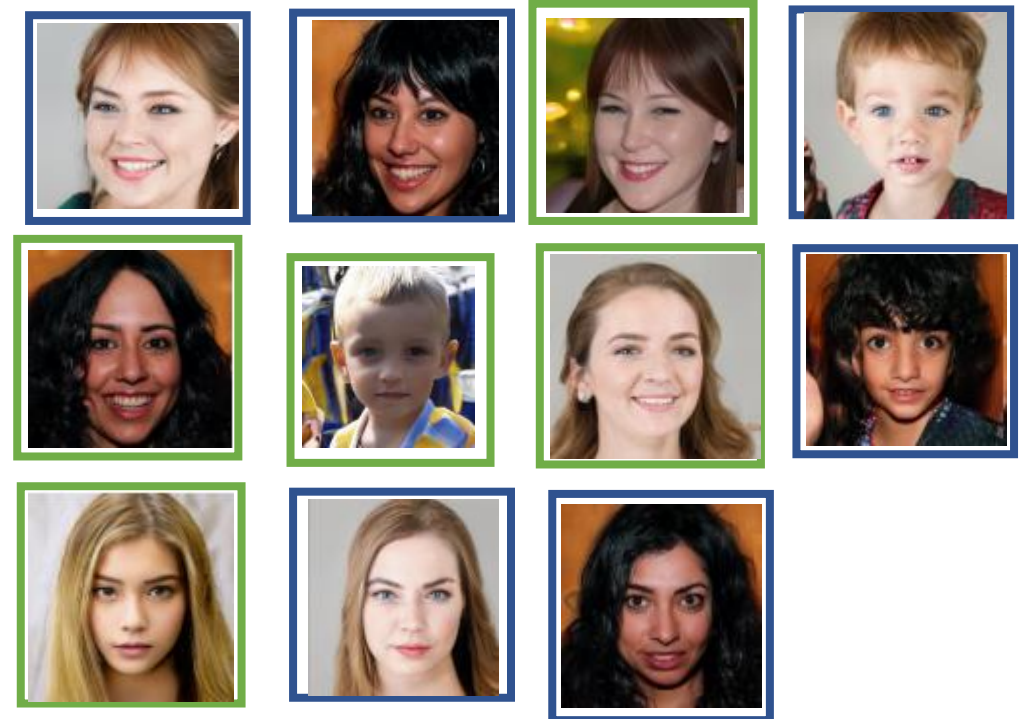


Real

Fake

## Discriminator

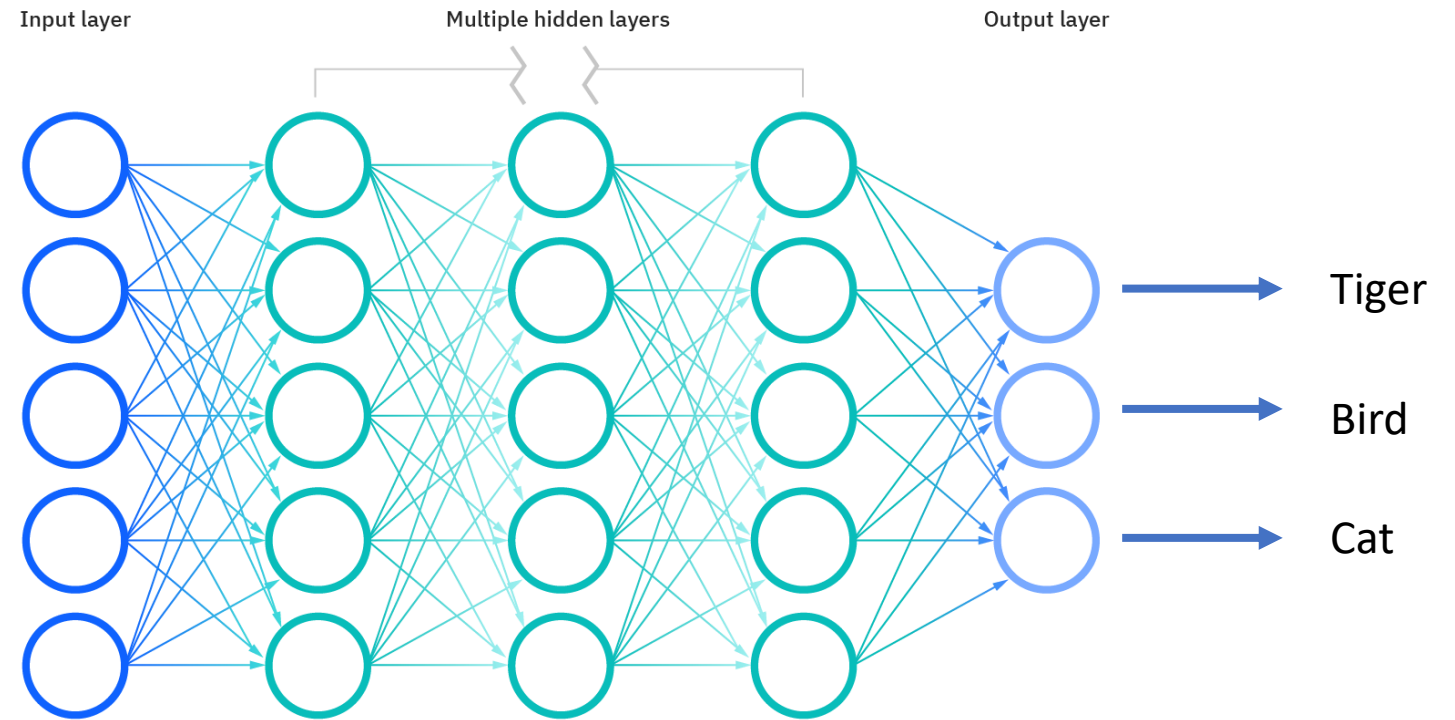
It will learn to distinguish **Real** from **Fake**  
It is like a **Art Inspector**



# Discriminator - Classifiers

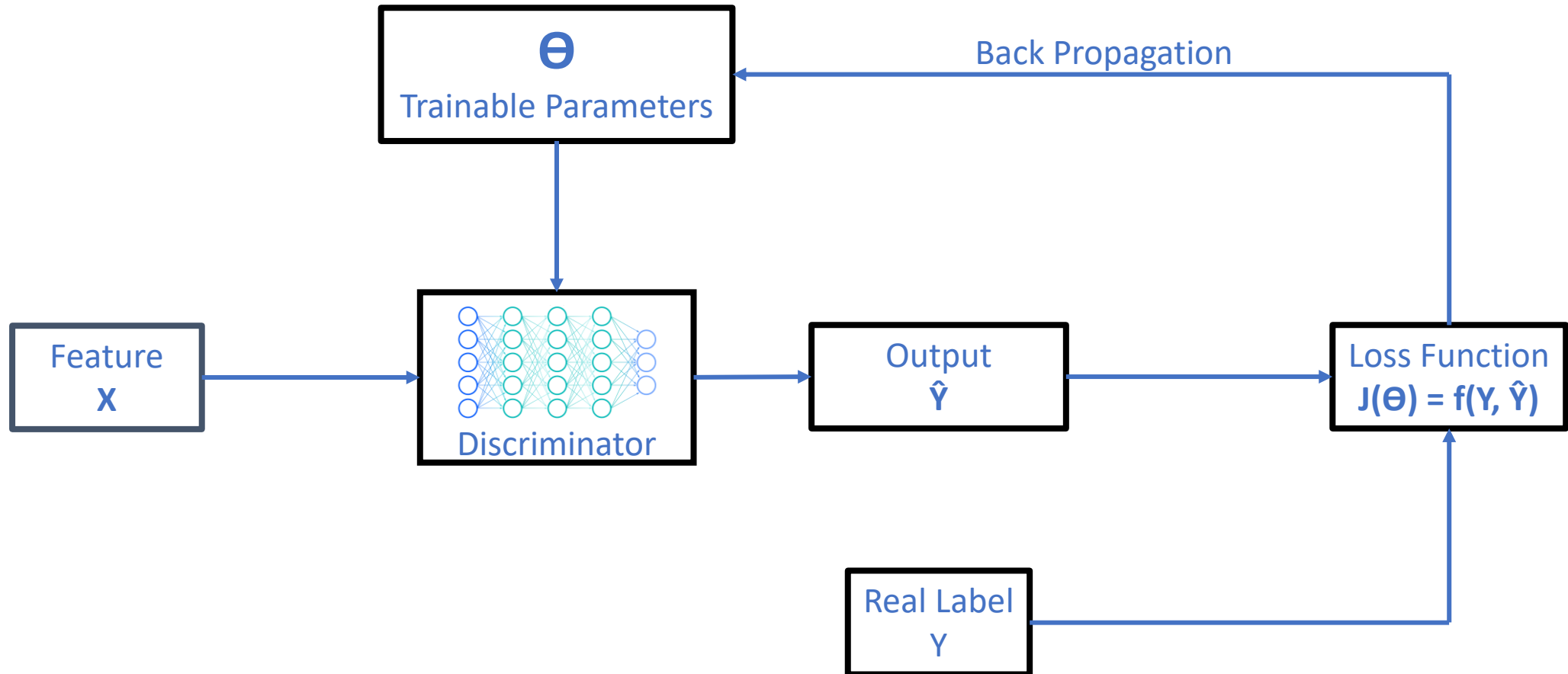


Ref: ImageNet



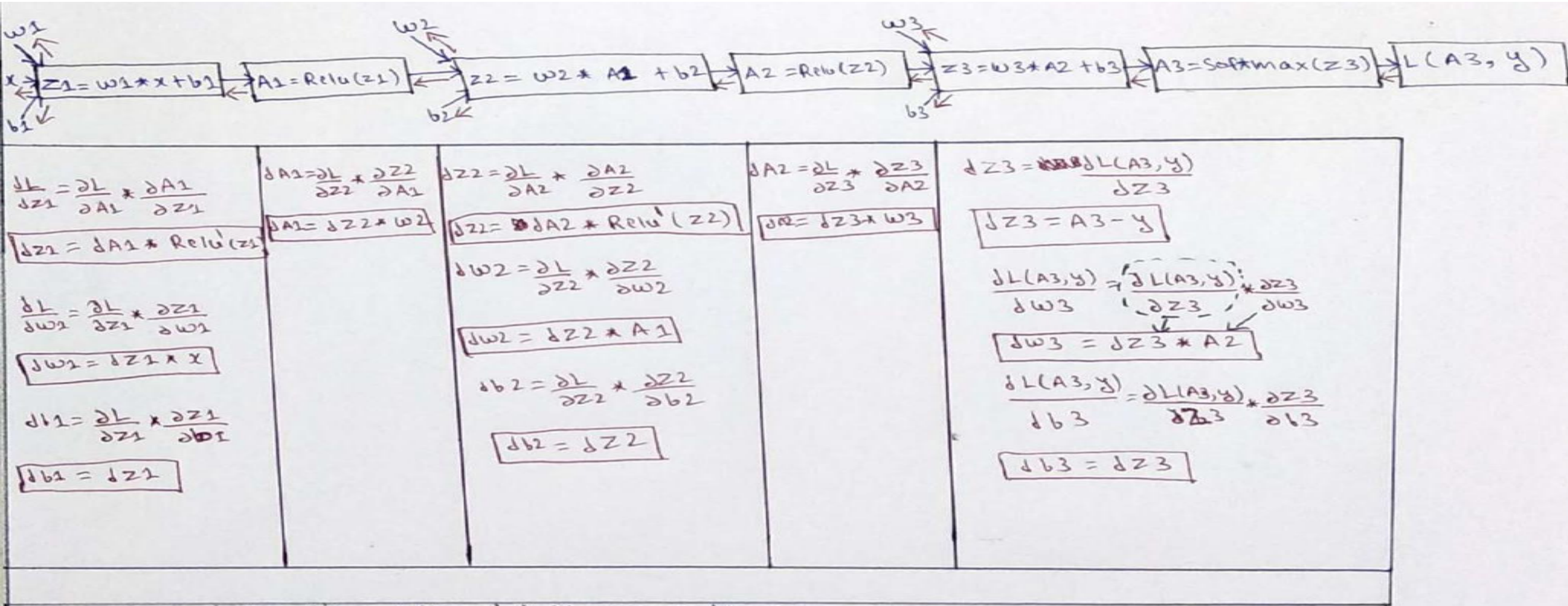
Ref: IBM

# Discriminator - Training





# Back Propagation Example



Loss function:  $L(A_3, y) \rightarrow \text{Cross-entropy}$

→ : It denotes forward propagation

← : It denotes Backward propagation

# Discriminator - Probability

$$P(\hat{Y}|X) = \frac{P(\hat{Y} \cap X)}{P(X)}$$

$\hat{Y}$  -> Predicted Class

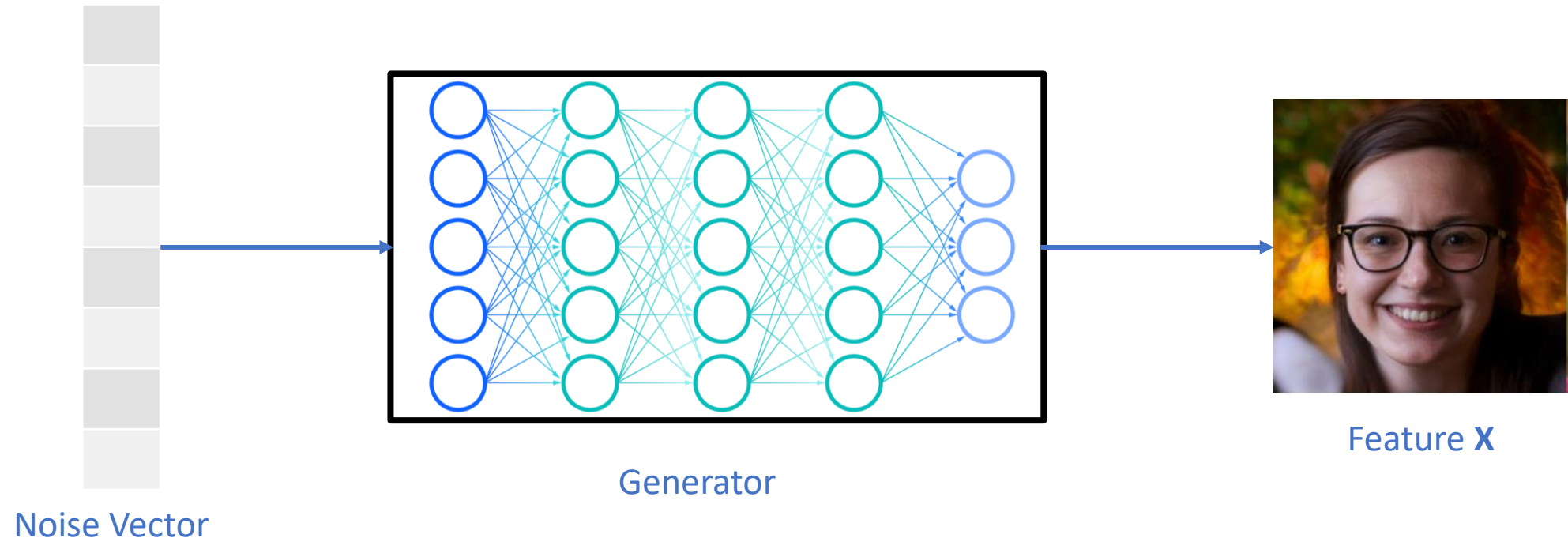
$X$  -> Features

$P(\textit{Real/Fake} |$



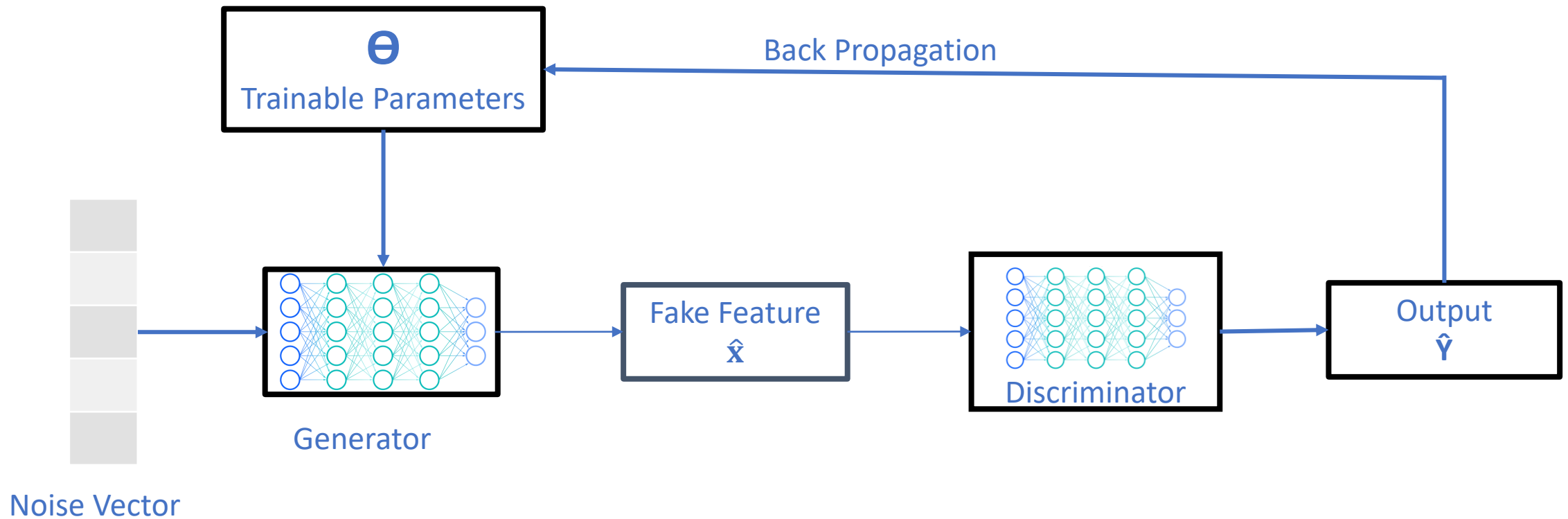
)

# Generator



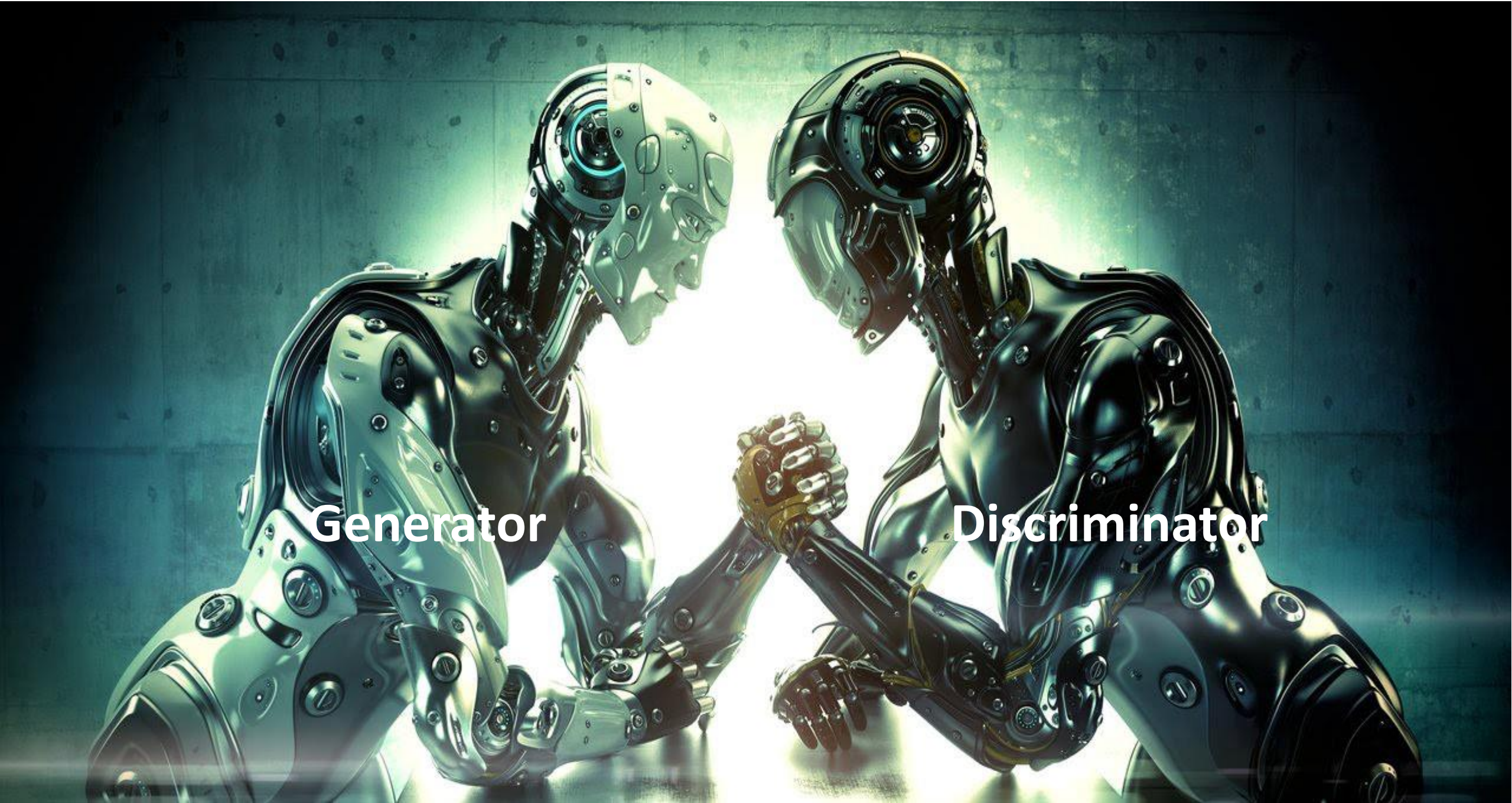


# Generator - Training



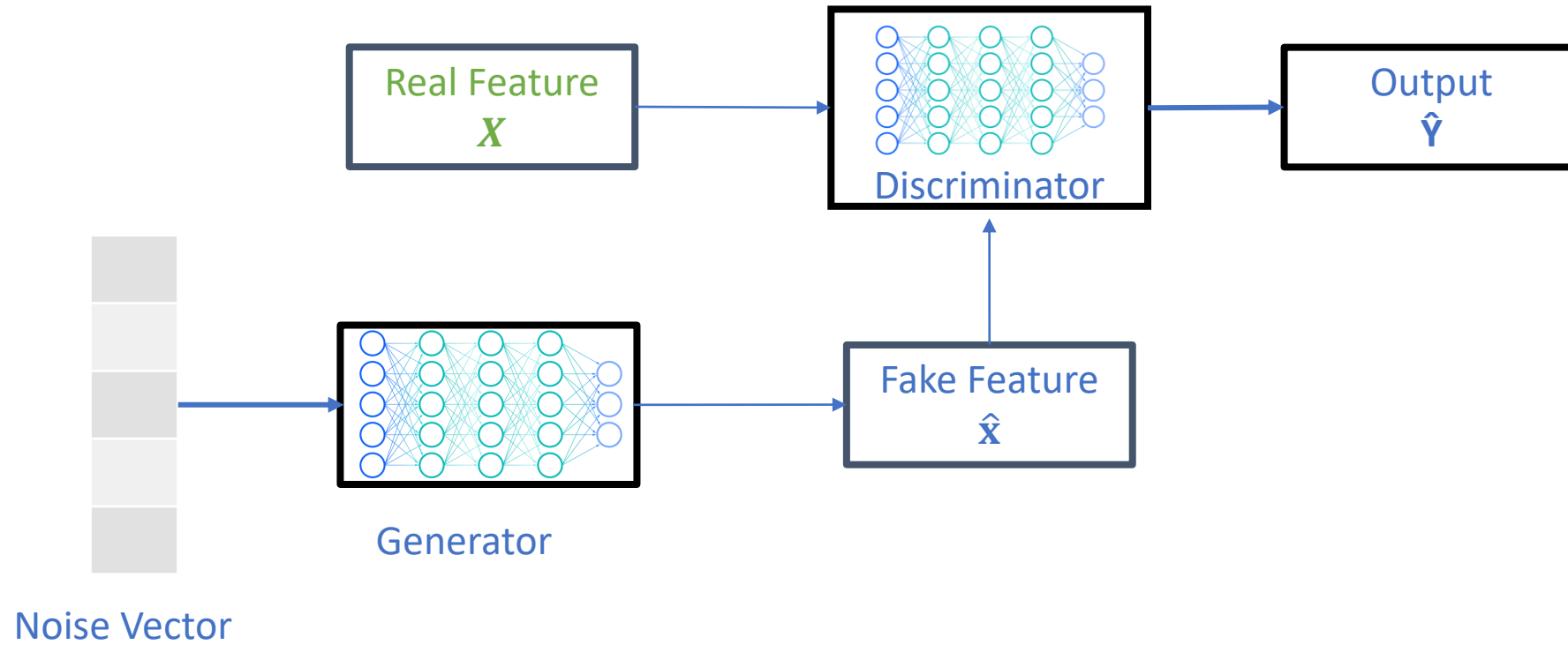
# Generator - Probability

$$P(\text{Image} | \text{Human})$$
$$P(\text{Image}) \rightarrow \text{Generate possible faces}$$





# GAN - Model



# Loss Function Example – Binary Cross Entropy

$$J(\theta) = -\frac{1}{m} \sum_{i=1}^m [y^{(i)} \log h(x^{(i)}, \theta) + (1 - y^{(i)}) \log(1 - h(x^{(i)}, \theta))]$$

Average Loss over whole batch

Prediction

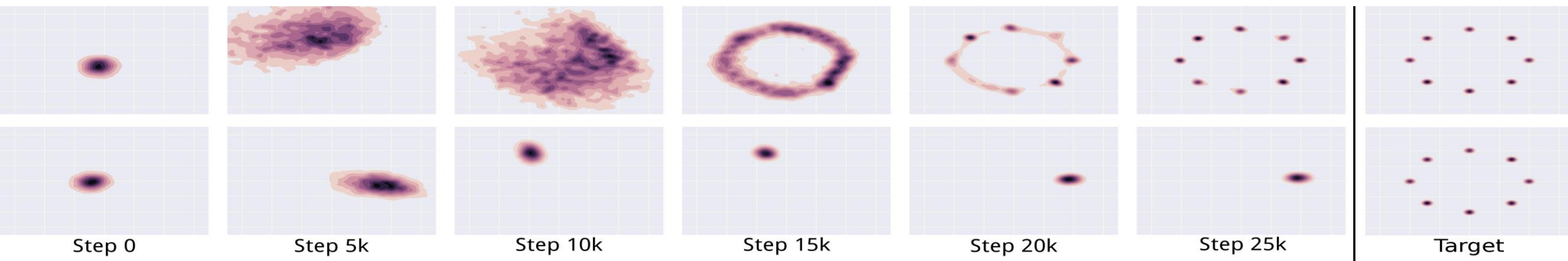
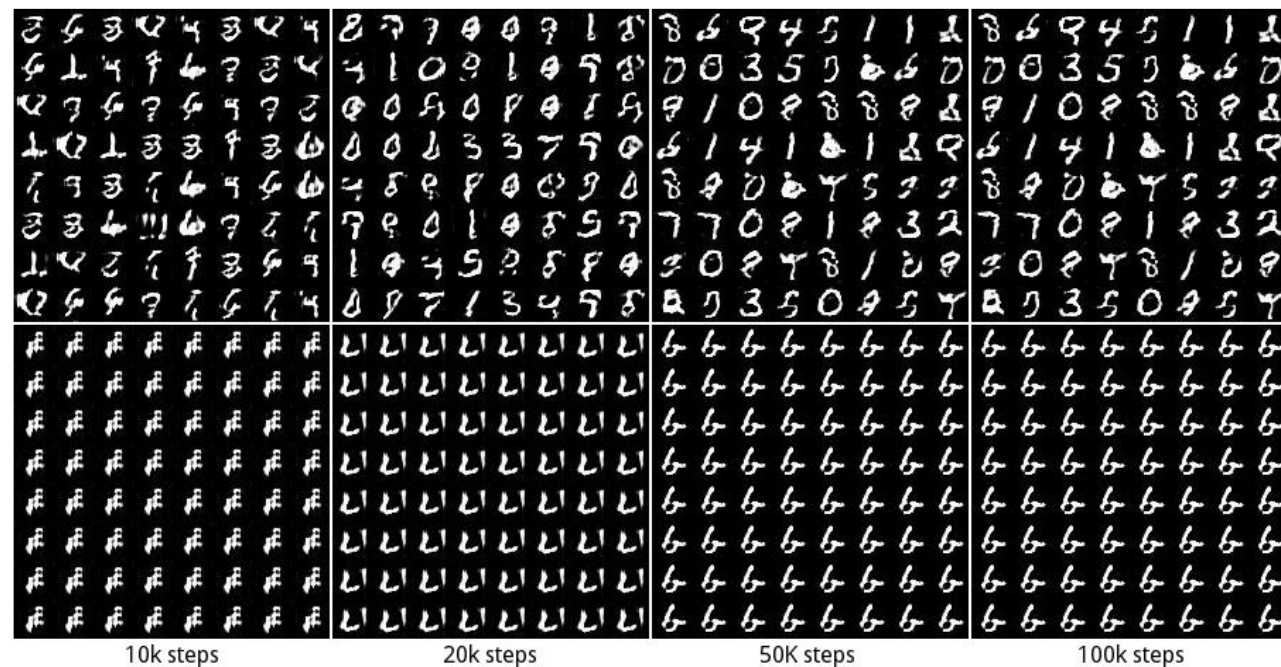
Labels

Features

Parameters

# Difficulties - Training

- Non Convergence
- Mode Collapse



Metz, Luke, et al.(2016) "Unrolled Generative Adversarial Networks."

# Major Types of GANS

- Conditional GAN
- InfoGAN
- DCGAN
- StackGAN
- Wasserstein GANs(WGAN)



# My Contributions to the Projects of GANs Domain

# Use Case1 – Malware Detection

- **Domain** : Novel Malware Generation and Detection
- **Paper** : Shobhit and P. Bera, "ModCGAN: A Multimodal Approach to Detect New Malware," 2021 International IEEE Cyber Science, Ireland
- **Youtube Link** : <https://www.youtube.com/watch?v=6-iwKgrKyPY>

# Use Case 2 : Image Sequence Generation from Text

Ground  
Truth



Generated  
Images



Story

The park  
was empty.

Many people  
entered the park.

After sometime,  
animals entered.

There were many  
children who  
were playing.

There was a food  
truck near it.

# Links – Applications of GANs Enjoy!

- <http://nvidia-research-mingyuliu.com/vid2vid-cameo/>
- <http://nvidia-research-mingyuliu.com/ganimal>
- <http://nvidia-research-mingyuliu.com/gaugan>
- <https://www.nvidia.com/research/inpainting/index.html>
- <https://www.wombo.ai/>



# Summary

- GANs are generative models that are implemented using two stochastic neural network modules: **Generator** and **Discriminator**.
- **Generator** tries to generate samples from random noise as input
- **Discriminator** tries to distinguish the samples from Generator and samples from the real data distribution.
- Both networks are trained adversarially to fool the other component. In this process, both models become better at their respective tasks.
- Can be trained using back-propagation for Neural Network based Generator/ Discriminator functions.
- Sharper images can be generated.
- Faster to sample from the model distribution: *single* forward pass generates a *single* sample.

Questions  
&  
Thank You