

# EI320A(3) 深度學習使用 Python

Instructors

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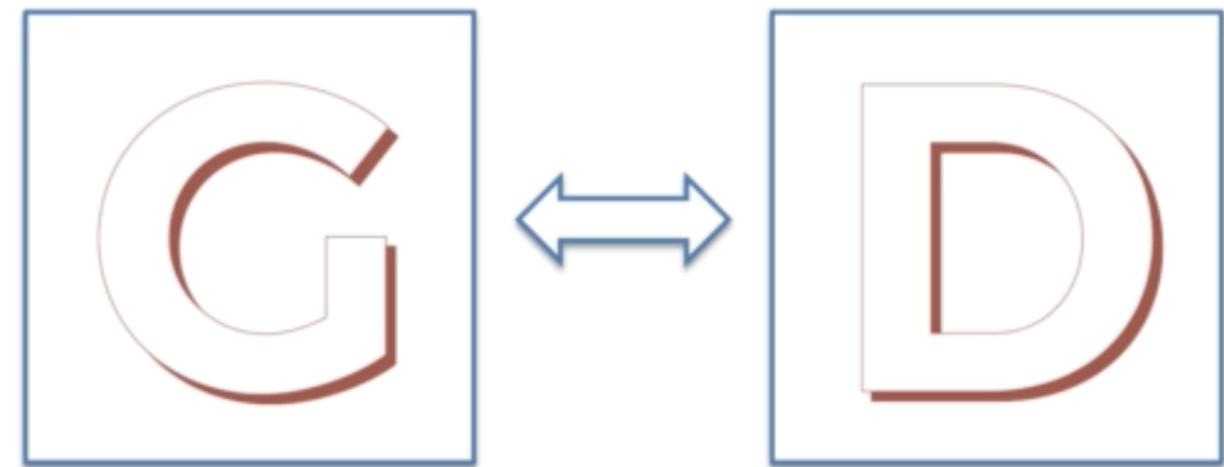
<b>Week</b>	<b>Date</b>	<b>Content</b>	<b>Note</b>	<b>Total</b>
1	2/26	Welcome to the course	Homework (1)	1
2	3/5	Crash Course of Python, NumPy, Pandas, and Matplotlib	In class hands-on (4)	5
3	3/12	Get to know about Data, ML: Classification Models	In class hands-on (5)	10
4	3/19	ML: Regression Models	In class hands-on (5)	15
5	3/26	ML: Clustering/Apriori Models	In class hands-on (5)	20
6	4/2	Holiday		
7	4/9	Introduction to Deep Learning (ANN)		
8	4/16	ANN Labs, Introduction to Convolutional Neural Network (CNN)	In class hands-on (10)	30
9	4/23	Convolutional Neural Network (CNN) & CNN Labs	In class hands-on (5)	35
10	4/30	Introduction to Recurrent Neural Network (RNN)	In class hands-on (5)	40
11	5/7	Recurrent Neural Network (RNN) & RNN Labs	In class hands-on (5)	45
12	5/14	Wrap Up all ANN, CNN, RNN <b>Project Proposal Presentation</b>	<b>Proposal Presentation (10)</b>	<b>55</b>
13	5/21	Generative Adversarial Network (GAN)	In class hands-on (5)	60
14	5/28	Reinforcement Learning (RL)	In class hands-on (5)	65
15	6/4	NLP & S2S & Attention Neural Network	In class hands-on (5)	70
16	6/11	N/A	In class hands-on (5)	75
17	6/18	<b>Final Project Presentation</b>	<b>Final Presentation (25)</b>	<b>100</b>

# GAN Plan of Attack

- The Idea Behind Generative Adversarial Networks (GANs)
- How Do GANs Work (3 Steps)
- Applications

# The Idea Behind GANs

Generative  
Adversarial  
Network

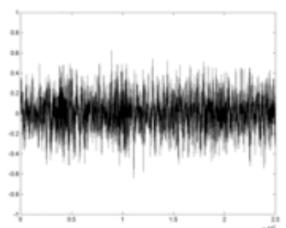


# GAN Plan of Attack

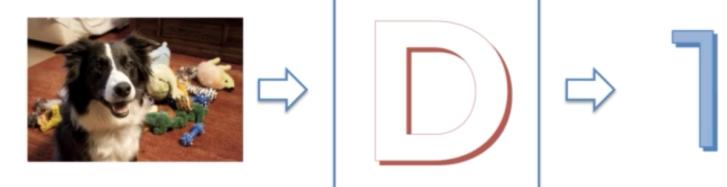
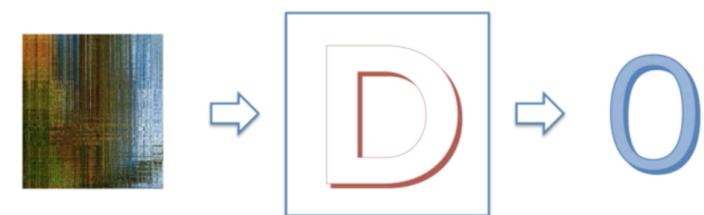
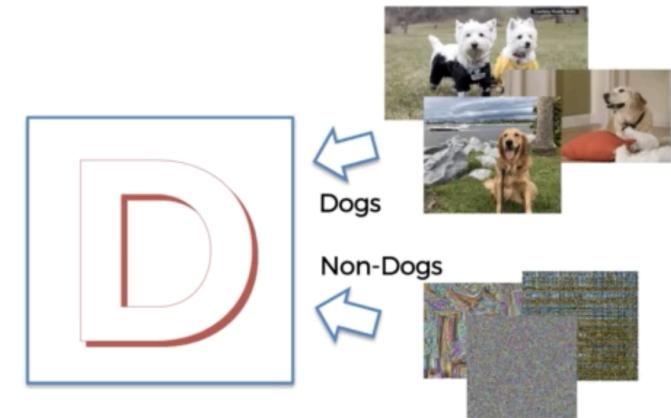
- The Idea Behind Generative Adversarial Networks (GANs)
- **How Do GANs Work (3 Steps)**
- Applications

# How Do GANs Work? (Step1)

## Generative

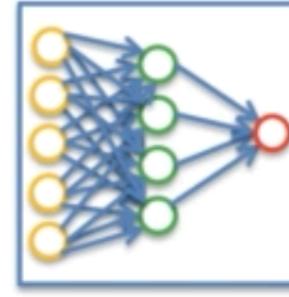
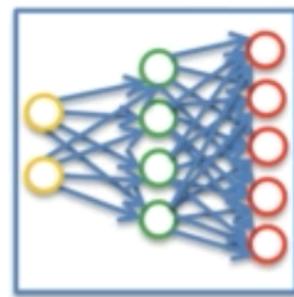


## Adversarial

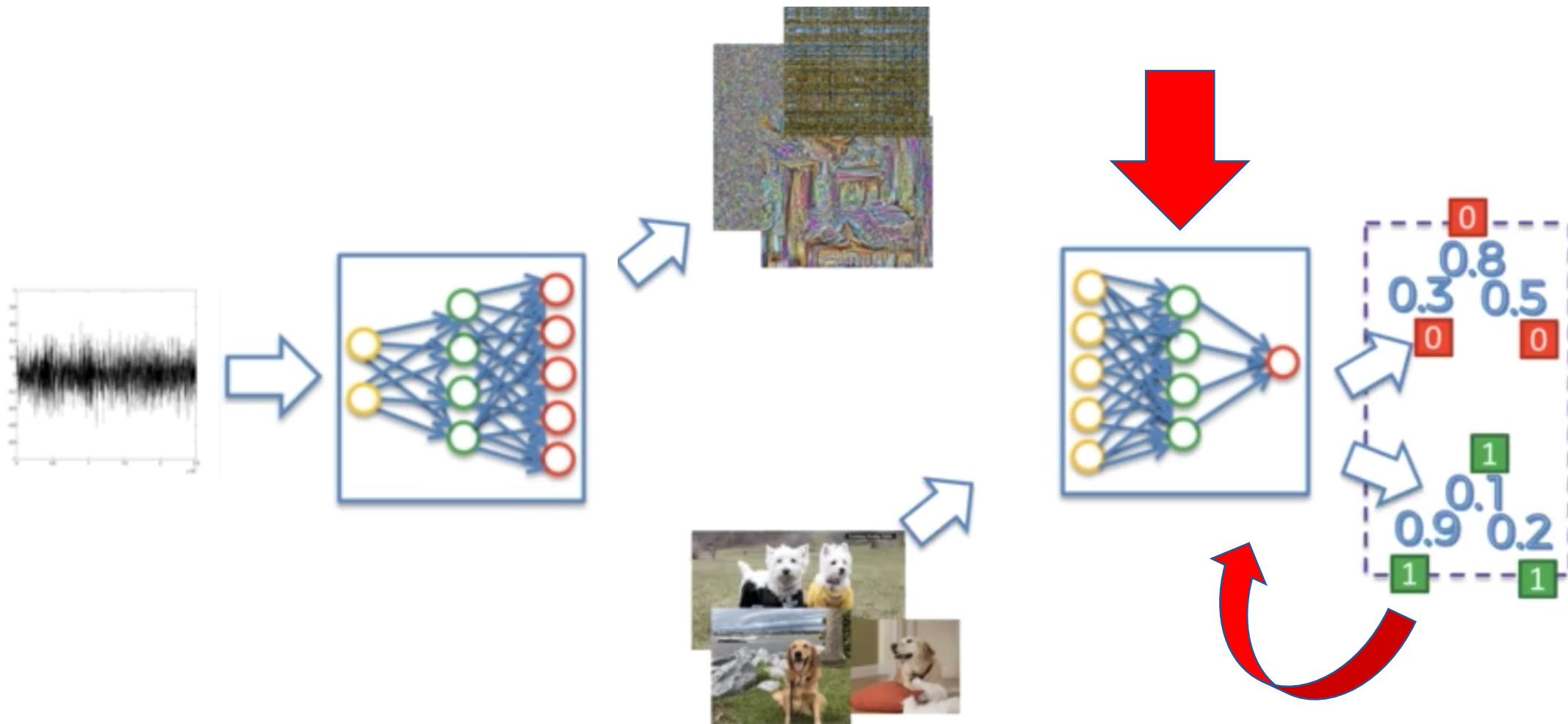


# How Do GANs Work? (Step1)

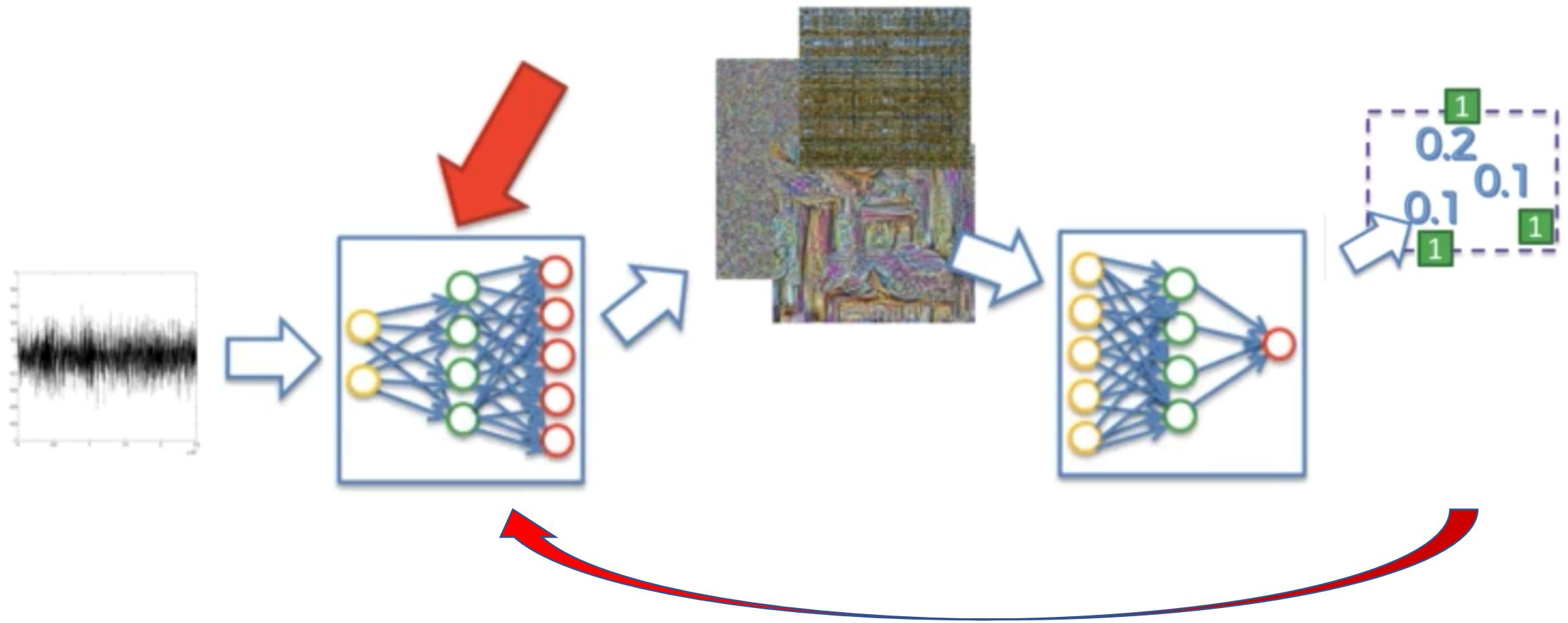
## Network



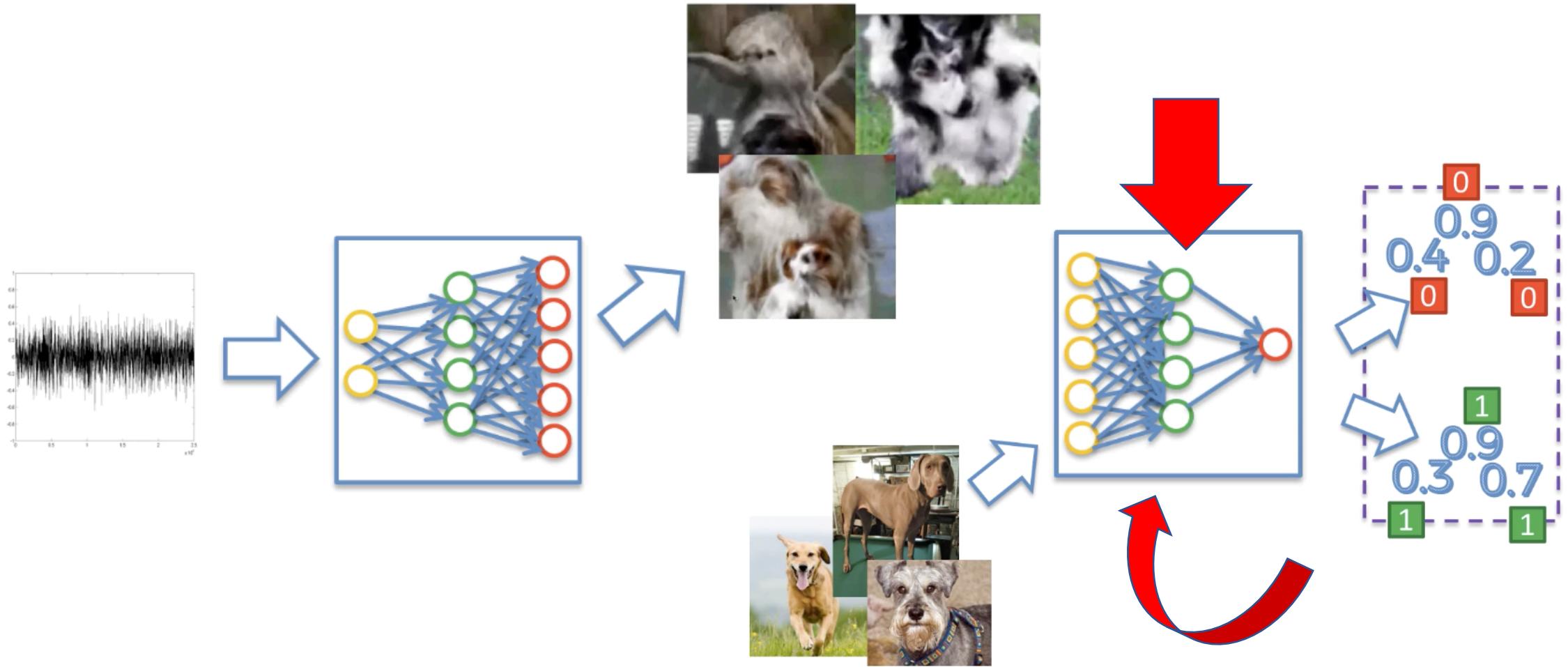
# How Do GANs Work? (Step1)



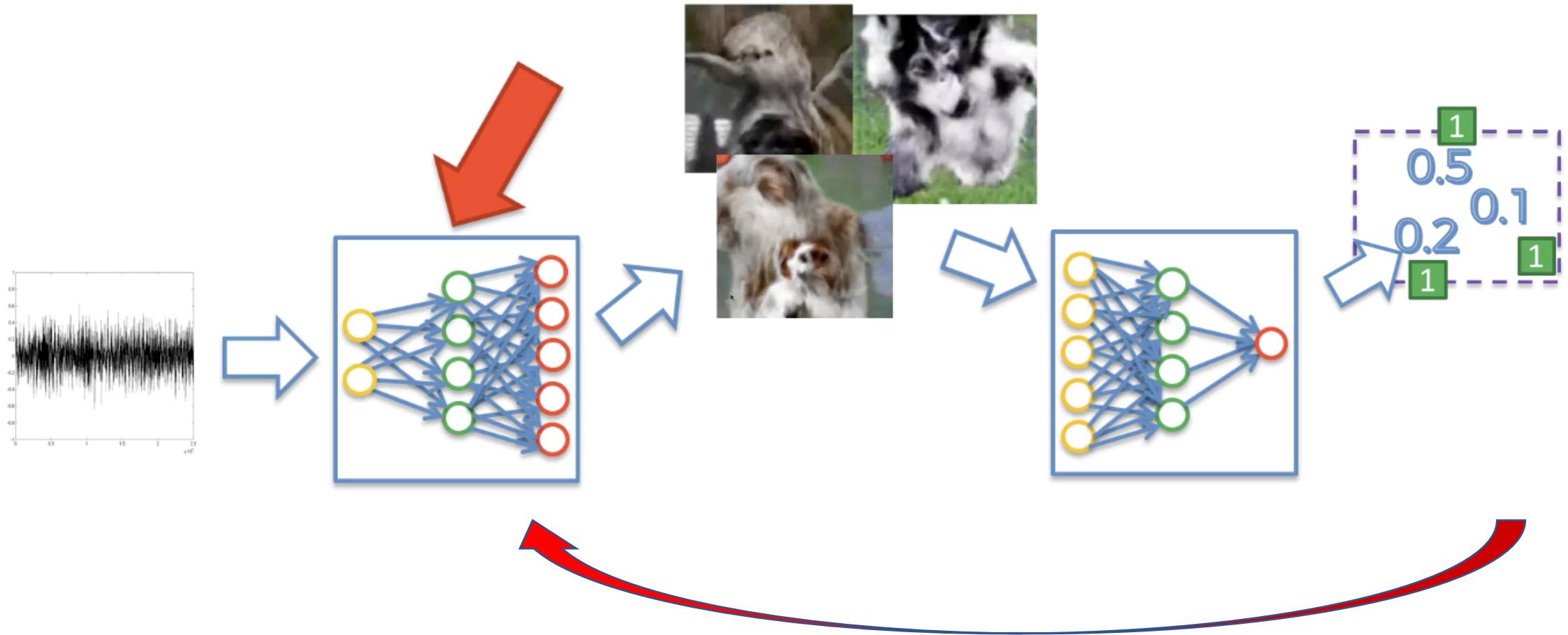
# How Do GANs Work? (Step1)



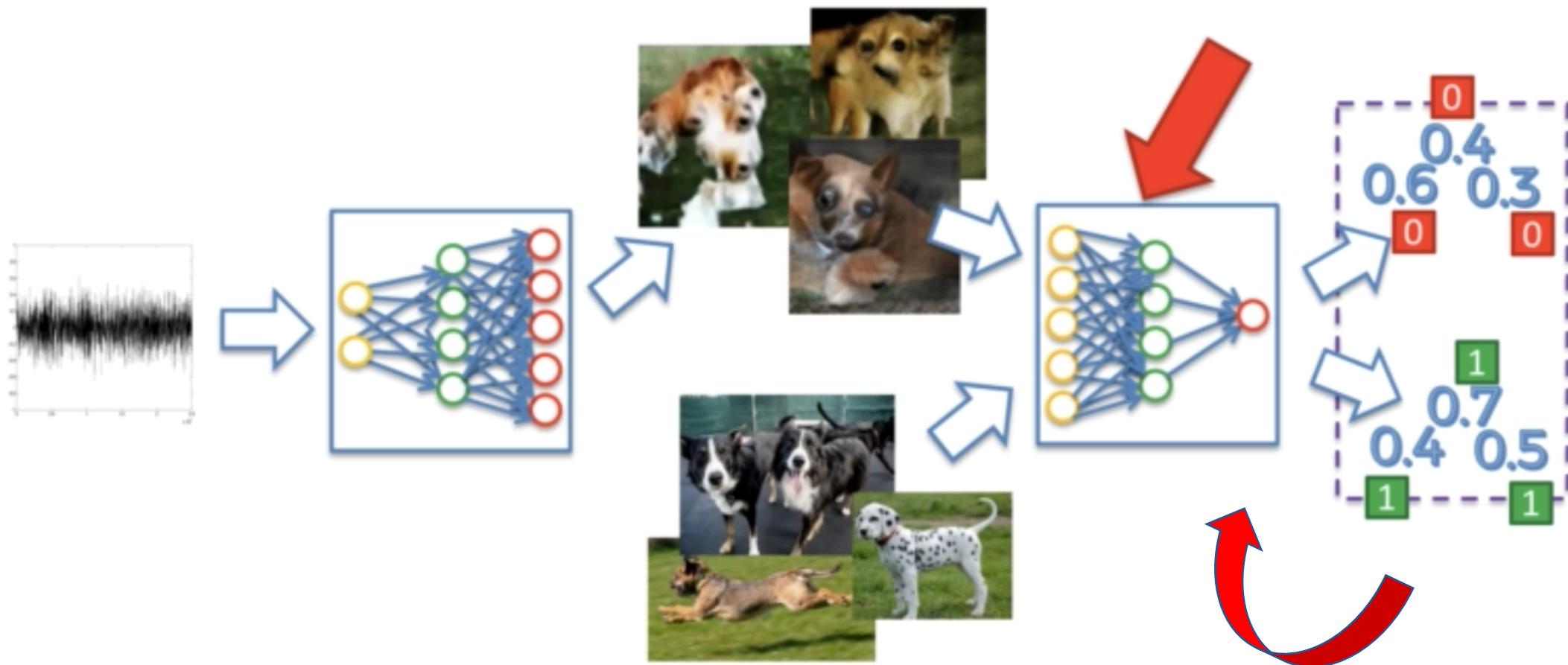
# How Do GANs Work? (Step2)



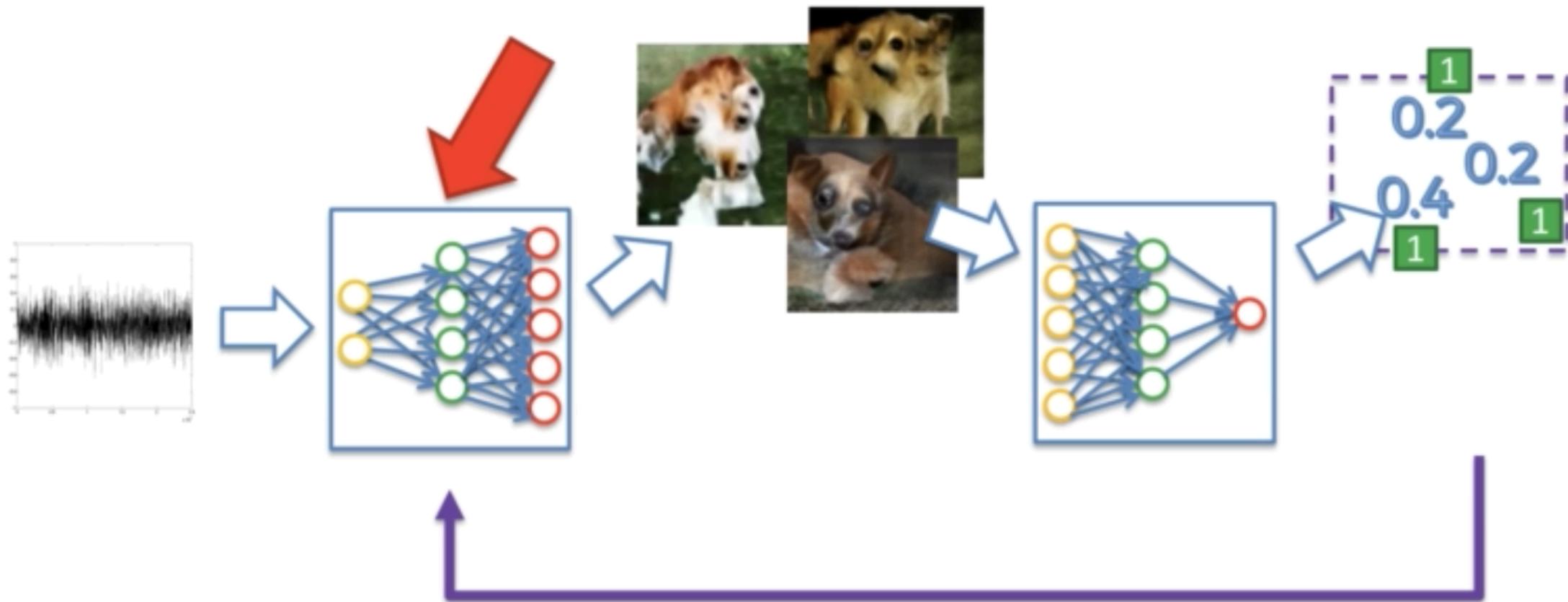
# How Do GANs Work? (Step2)



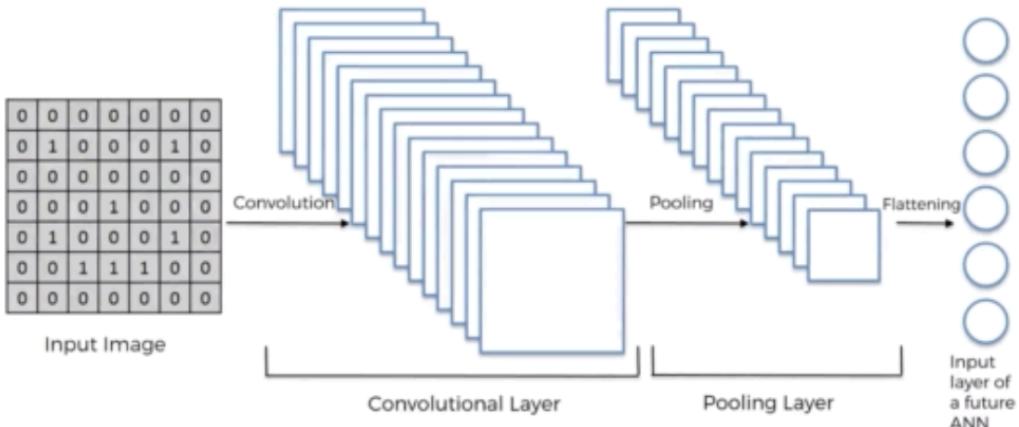
# How Do GANs Work? (Step3)



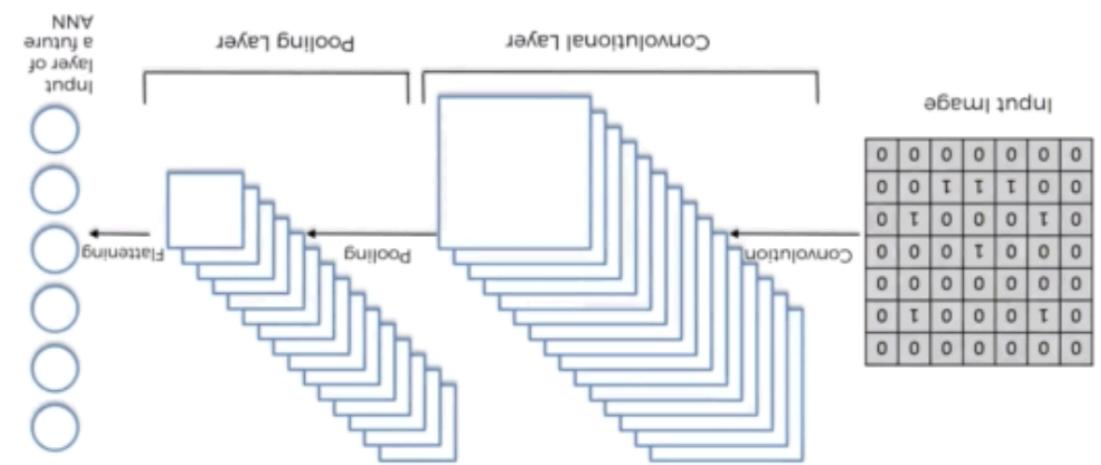
# How Do GANs Work? (Step3)



## Convolutional Neural Network



## DeConvolutional Neural Network



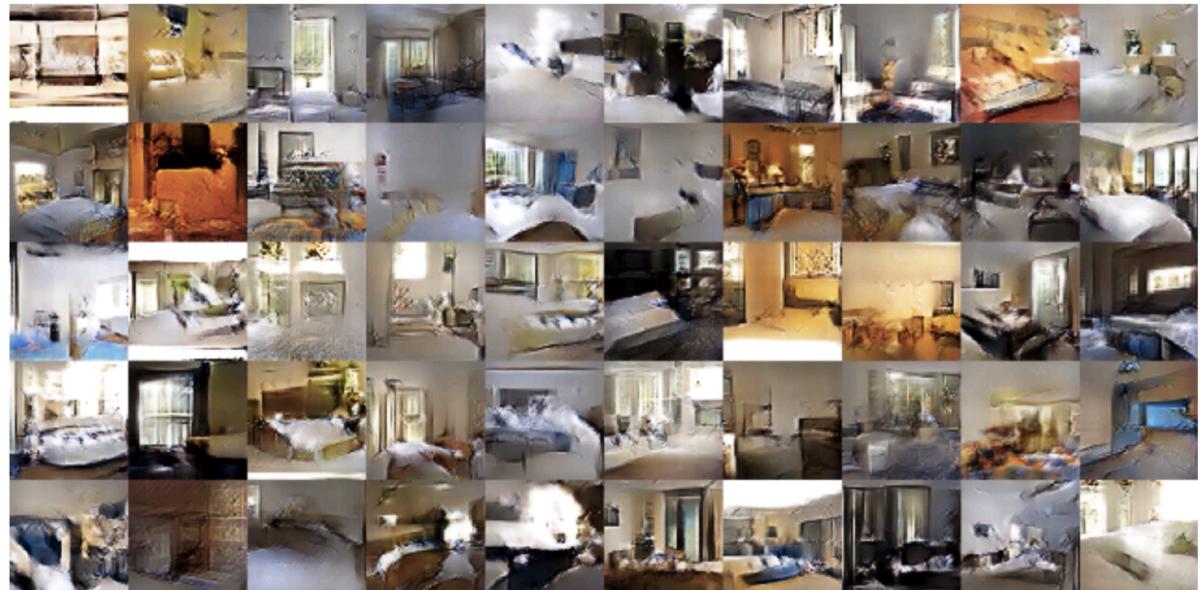
# GAN Plan of Attack

- The Idea Behind Generative Adversarial Networks (GANs)
- How Do GANs Work (3 Steps)
- **Applications**

# GAN Application

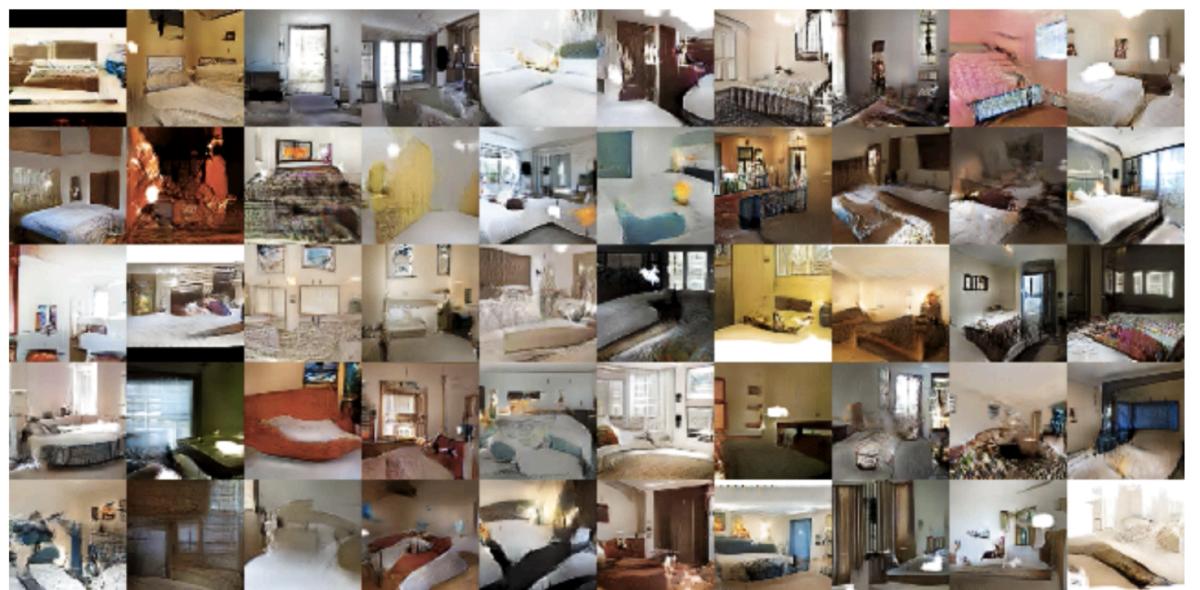
- Generating Images
- Image Modification
- Super Resolution
- Assisting Artists
- Phot—Realistic Images
- Speech Generation
- Face Ageing

# Generating Images



Source: <https://arxiv.org/pdf/1511.064>

@1Epoch



Source: <https://arxiv.org/pdf/1511.06434.pdf>

@10Epoch

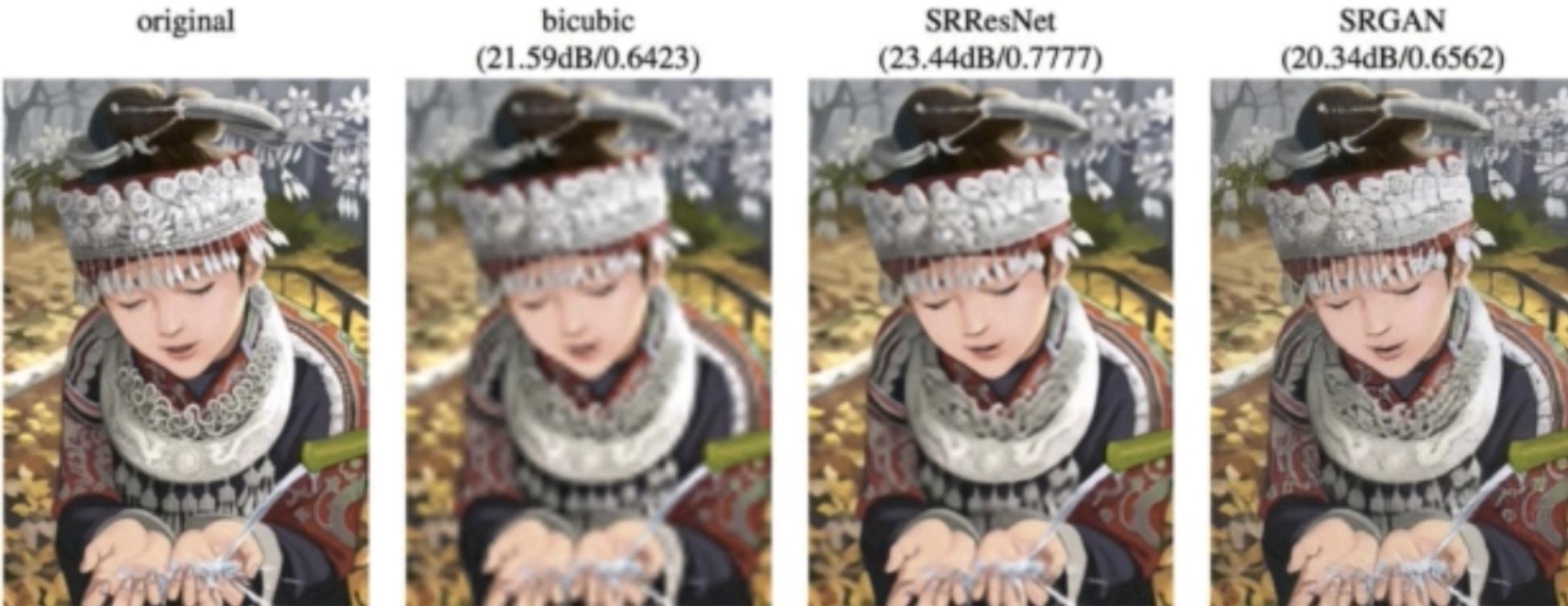
# Image Modification

A diagram illustrating image modification through addition. On the left, three input images are shown: a smiling woman, a neutral woman, and a neutral man. These are followed by a minus sign, a plus sign, and an equals sign. To the right of the equals sign is a grid of nine images labeled "smiling man". Above each image in the grid is a small stack of four images, suggesting a latent space representation where the top row shows the woman's features and the bottom row shows the man's features.

A diagram illustrating image modification through subtraction. On the left, three input images are shown: a man with glasses, a man without glasses, and a woman without glasses. These are followed by a minus sign, a plus sign, and an equals sign. To the right of the equals sign is a grid of nine images labeled "woman with glasses". Above each image in the grid is a small stack of four images, suggesting a latent space representation where the top row shows the woman's features and the bottom row shows the man's features.

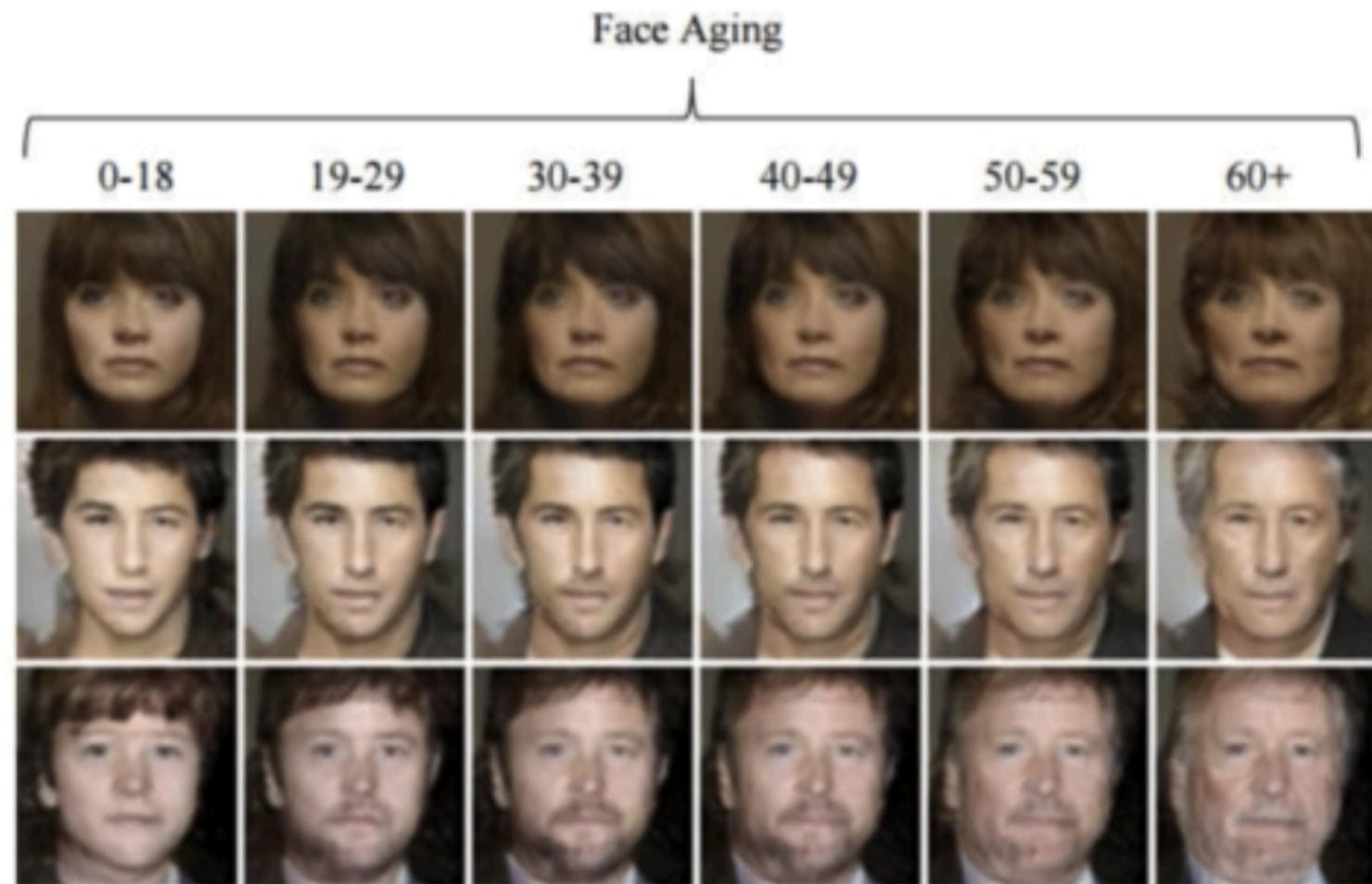
Two diagrams comparing image modification results. The top diagram shows the result of performing the same arithmetic operations (subtraction and addition) in the latent space (represented by the stack of images above) versus pixel space (represented by the raw images below). The result in pixel space is a man with glasses. The bottom diagram shows a similar comparison, resulting in a woman with a mustache.

# Super Resolution



*Source: Ian Goodfellow's presentation*

# Face Ageing



# Summary

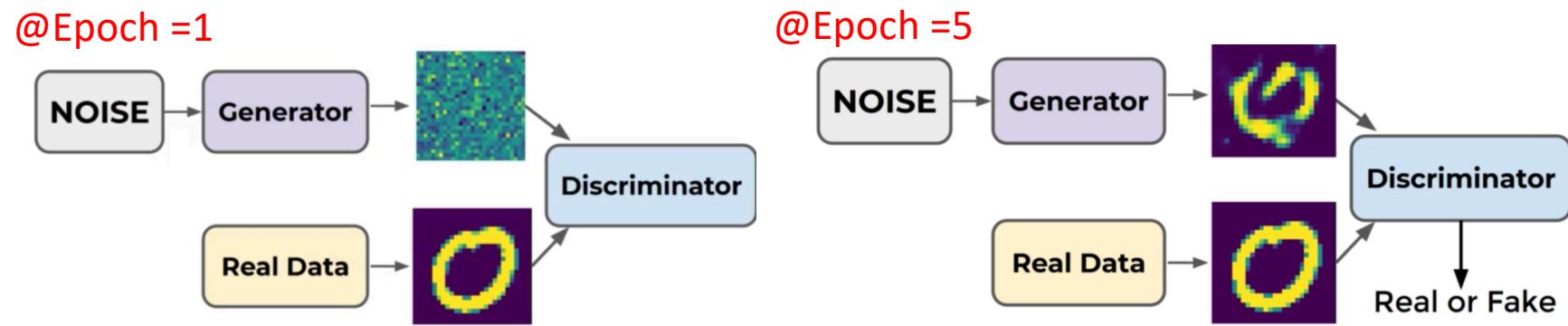
## Generator:

- Receives random noise (Gaussian Distribution)
- Outputs data (often an image)

## Discriminator

- Takes a dataset consisting of Real images from the real datasets and Fake images from generator.
- Attempt to classify real vs. fake images (always binary classification)

# Summary



## Training Phases:

- Phase1 – Train Discriminator
  - Real images (labeled 1) are combined with fake images from generator (labeled 0)
  - Discriminator trains to distinguish real from fake (with backpropagation only on discriminator weights)
- Phase2 – Train Generator
  - Produce fake images with generator
  - Feed only these fake images to discriminator with all labels set to 1 (real)
  - This causes the generator to produce images the discriminator believes to be real.
  - Because we feed in fake images with labeled 1, we **only** perform backpropagation on the generator weights in this step.

# Summary

- Keep in mind, the generator **never** gets to see the actual real images!
- It generates convincing images only based on gradients flowing back through the discriminator.
- Also, the discriminator is improving as training phases continuing, meaning the generated images will also need to get better and better.

Demo →

# Additional reading:

- Chanchana Sornsoontorn, 2017, [How do GANs intuitively work?](#)
- Ian Goodfellow et al., 2014, [Generative Adversarial Nets](#)
- Matthew D. Zeiler et al., 2011, [Adaptive Deconvolutional Networks for Mid and High Level Feature Learning](#)
- Alec Radford et al., 2015, [Unsupervised Representation Learning With Deep Convolutional Generative Adversarial Networks](#)
- ARTIST Vs. PIX2PIX - Is This Humor Or Horror?! [YouTube Video](#)