Introduction to Deep Learning for Computer Vision

Adhyayan '23 - ACA Summer School
Department of Computer Science and Engineering
Indian Institute of Technology Kanpur

Lecture 7

Generative Adversarial Network (GAN)

Generative Adversarial Networks

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Which one is fake?

GANs: What if we just want to sample?

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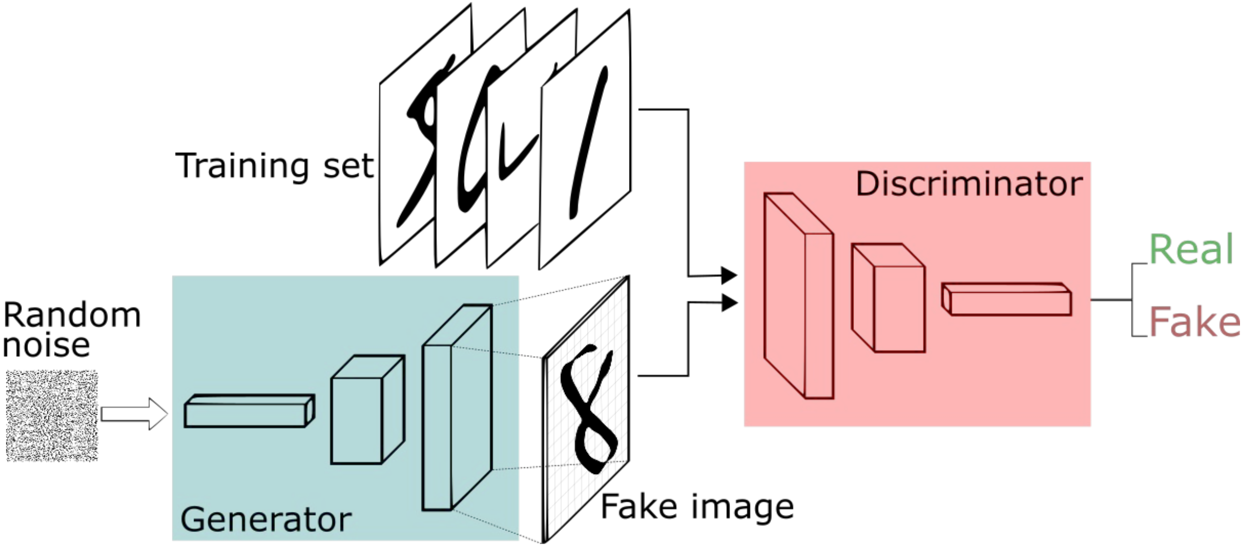
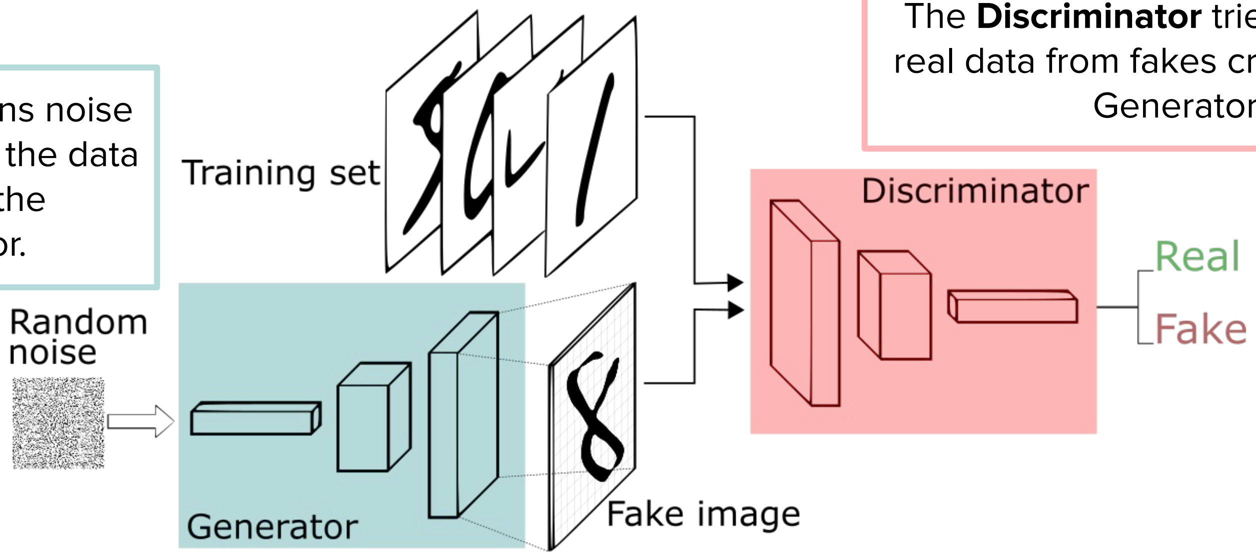


Generative Adversarial Networks (GANs)

GANs are a way to make a generative model by making two neural networks compete with each other.

The **Discriminator** tries to identify real data from fakes created by the Generator.

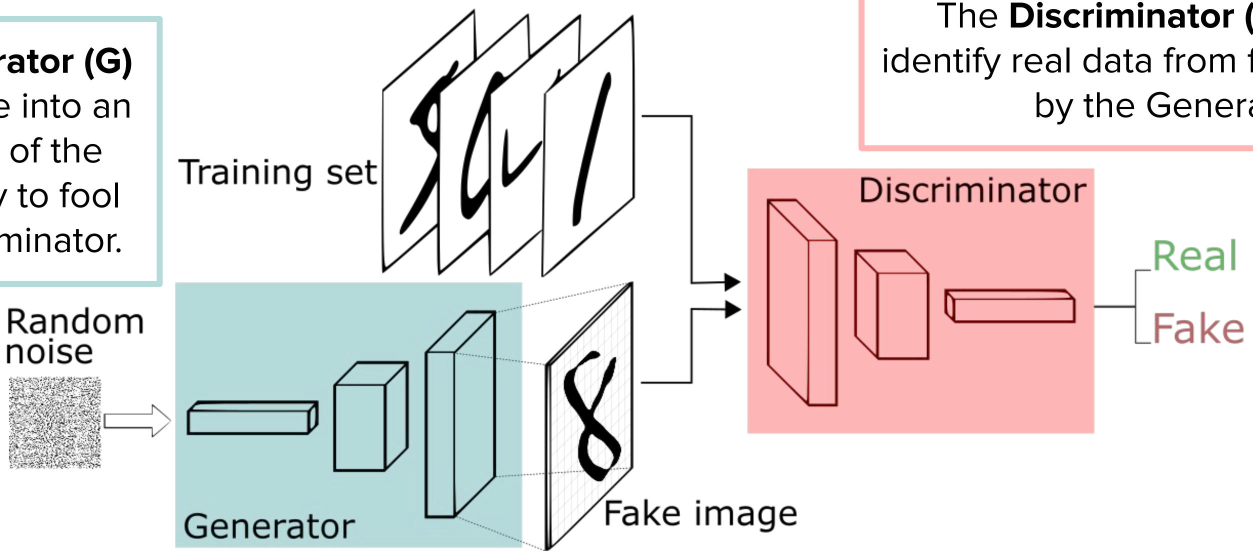
The **Generator** turns noise into an imitation of the data to try to fool the Discriminator.



Training GANs

The **Generator (G)** turns noise into an imitation of the data to try to fool the Discriminator.

The **Discriminator (D)** tries to identify real data from fakes created by the Generator.



Training: adversarial objectives for **D** and **G**.

Global Optimum: **G** reproduces the true distribution.

Training GANs

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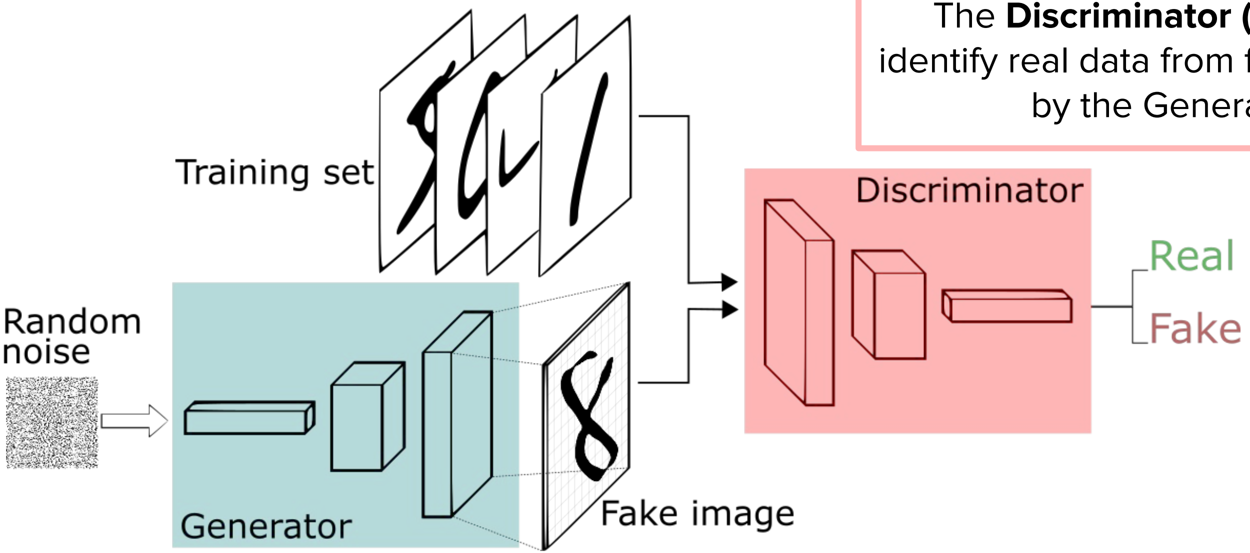

$$\text{argmax}_D \mathbb{E}_{\mathbf{z},\mathbf{x}}[\log D(G(\mathbf{z})) + \log(1 - D(\mathbf{x}))]$$

Fake

Real

Training GANs

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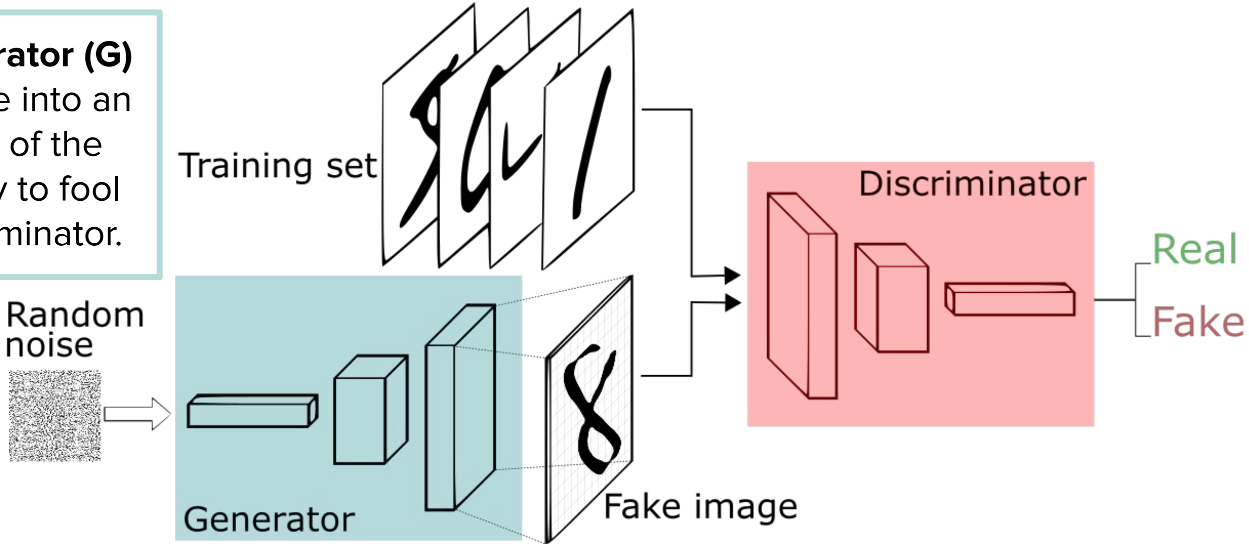
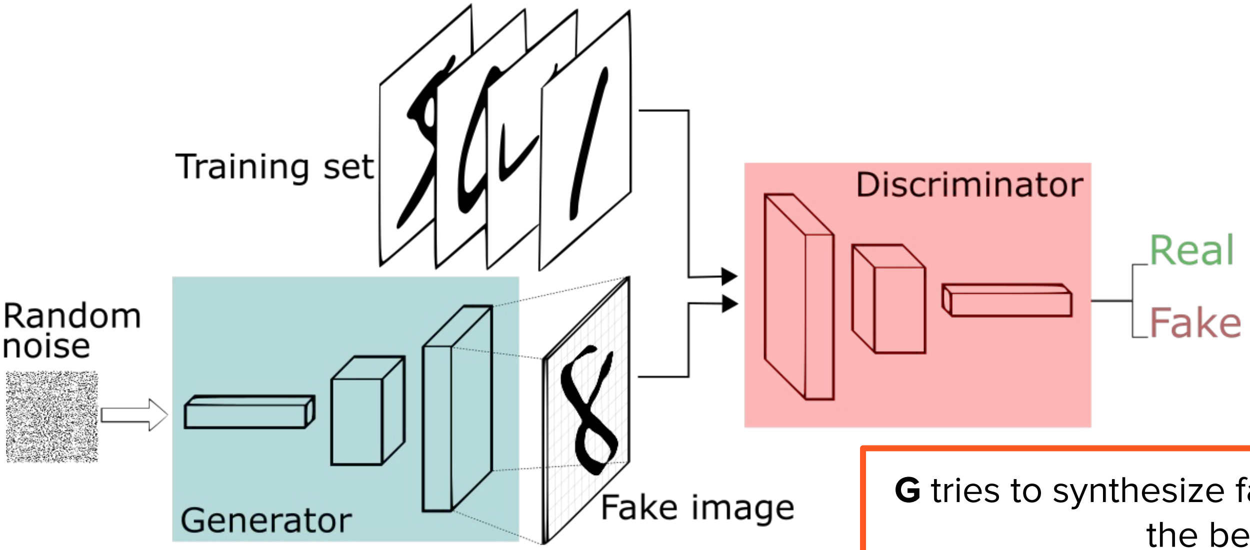


$$\mathrm{argmin}_G \mathbb{E}_{\mathbf{z},\mathbf{x}}[\log D(G(\mathbf{z})) + \log(1 - D(\mathbf{x}))]$$

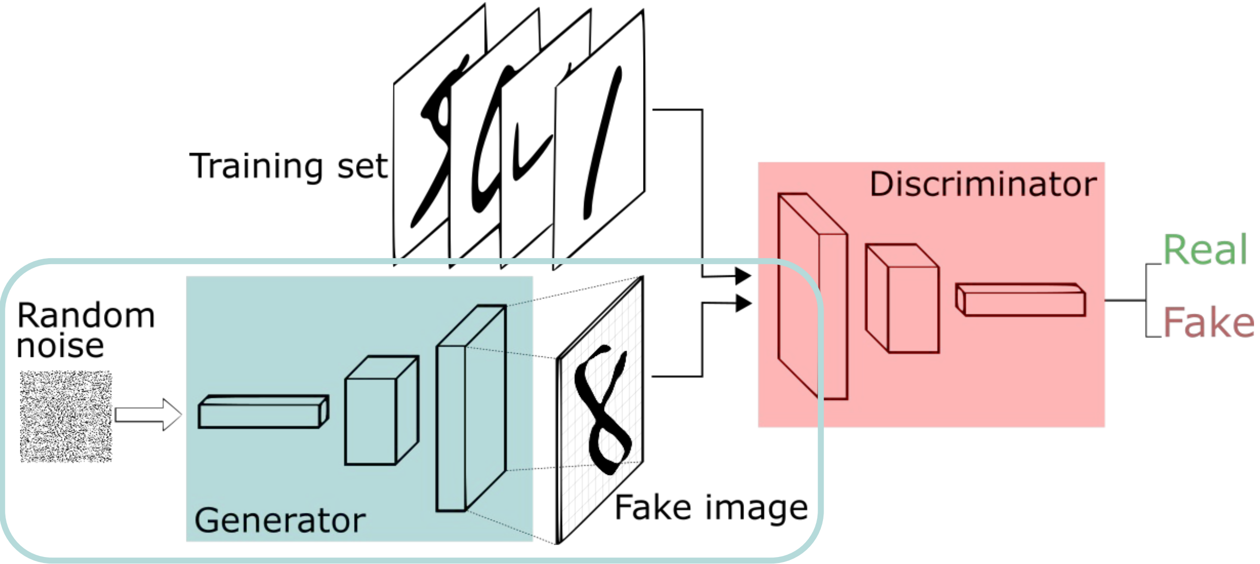
Training GANs



G tries to synthesize fake images that fool the best **D**.

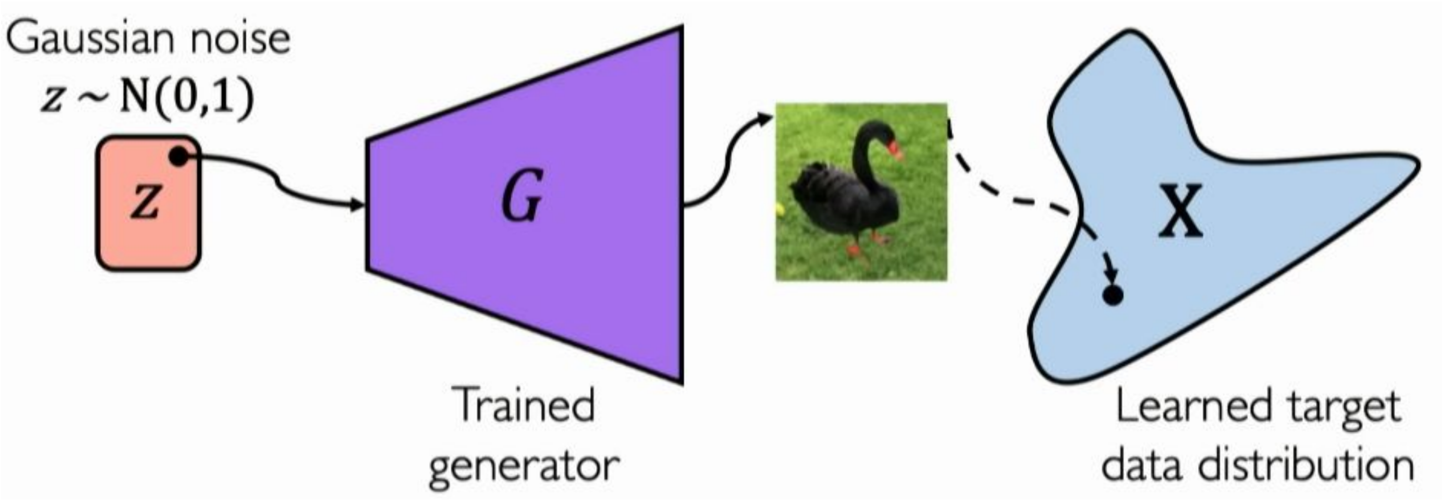
$$\text{argmin}_G \text{max}_D \mathbb{E}_{\mathbf{z},\mathbf{x}}[\log D(G(\mathbf{z})) + \log(1 - D(\mathbf{x}))]$$

Generating New Data from GANs

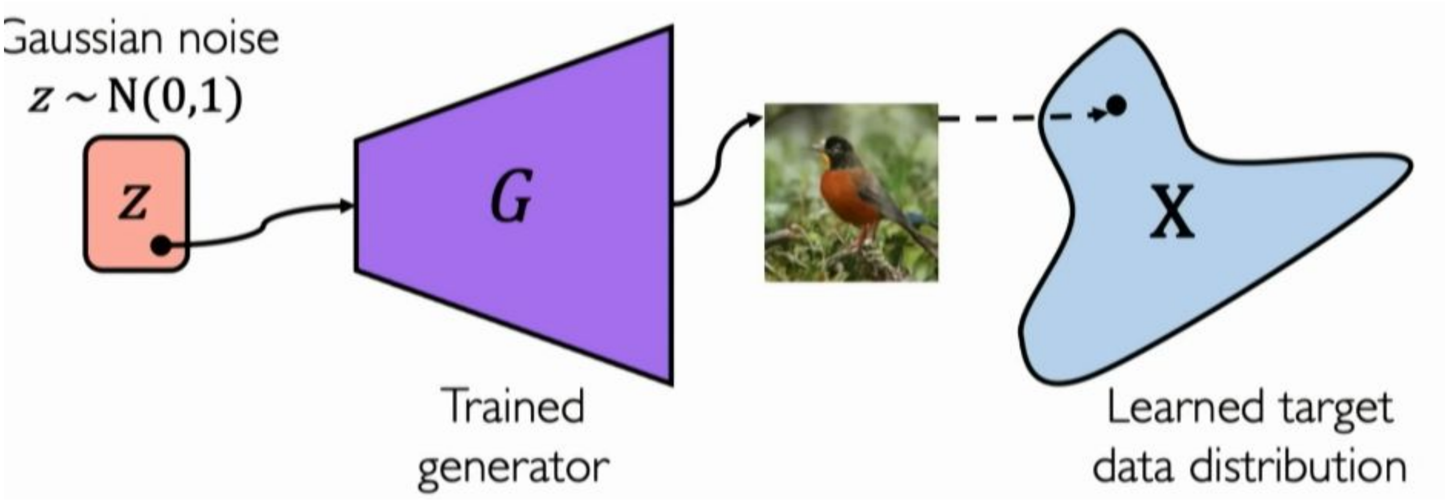


After training, use the generator network to generate **new data** that has never been seen before!

GANs are Distribution Transformers



GANs are Distribution Transformers



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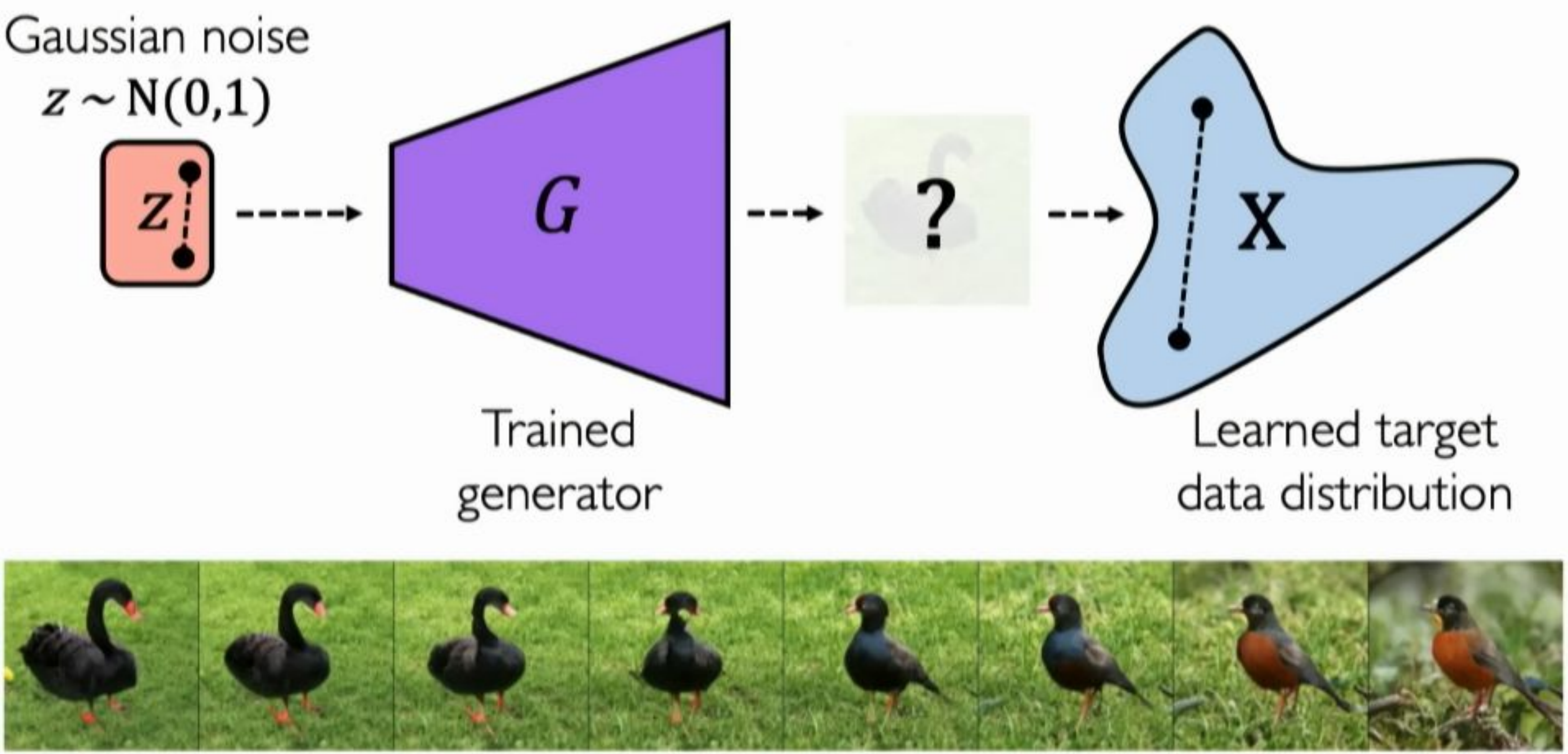
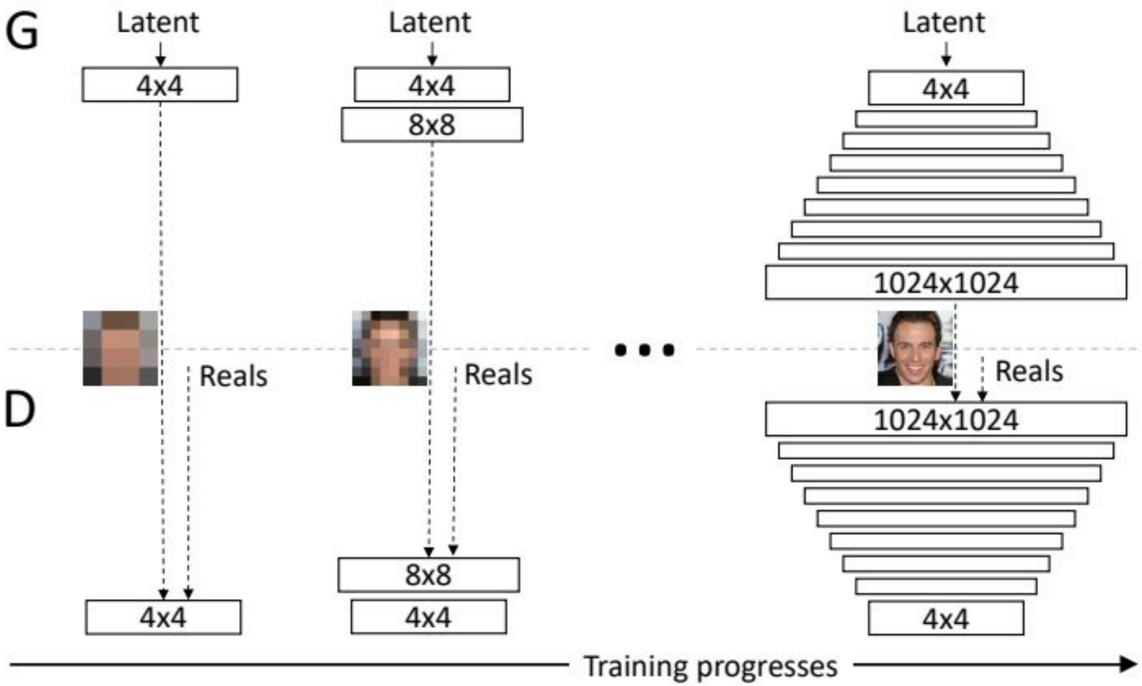
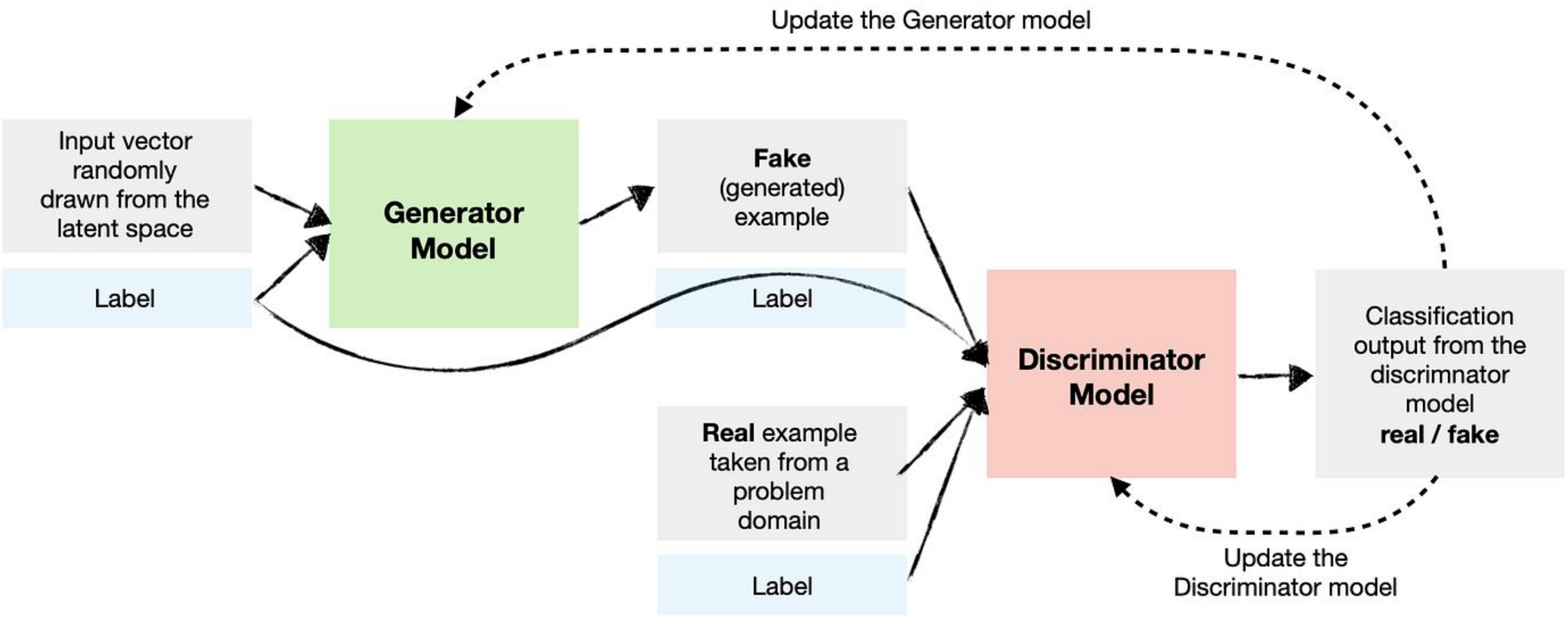


Progressively Growing GANs

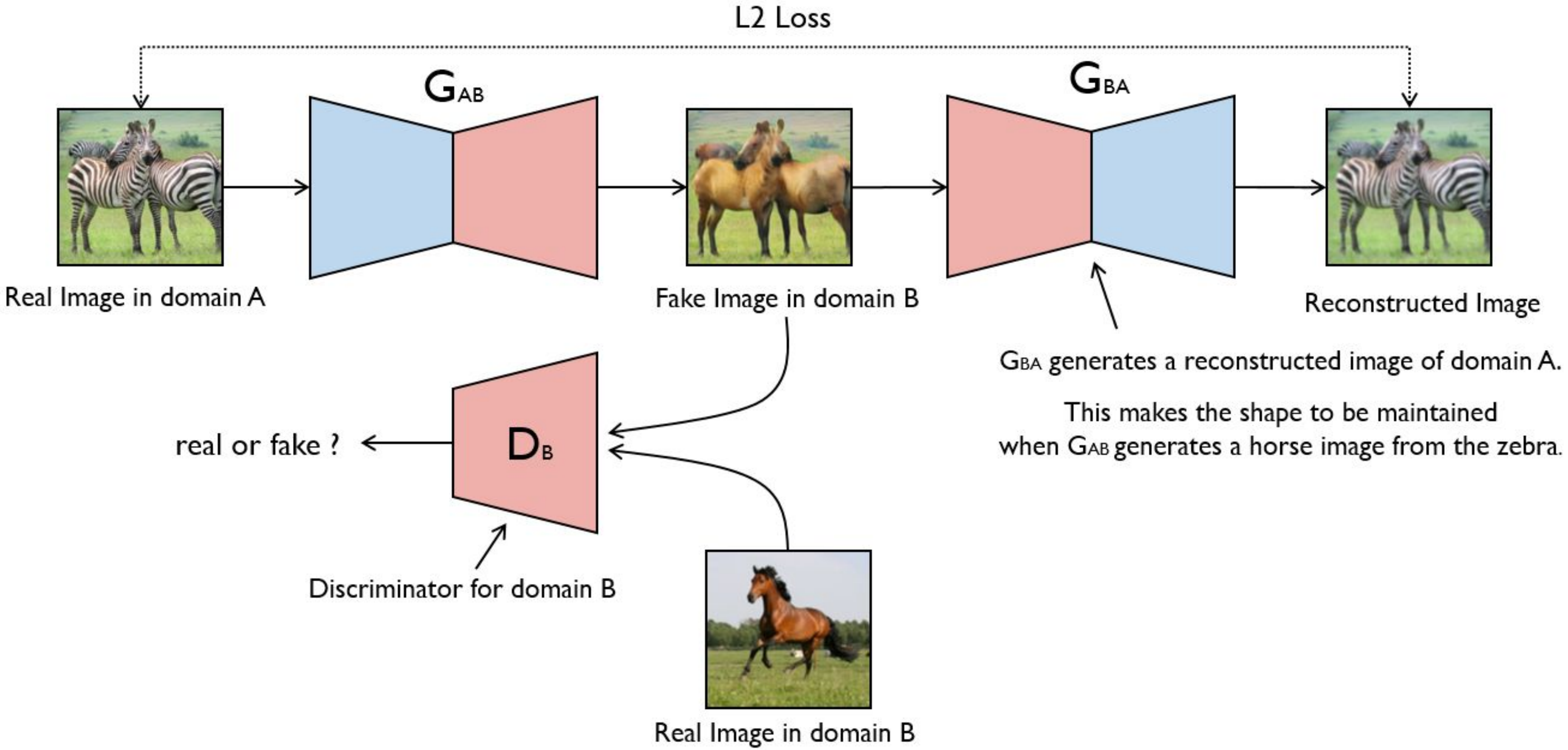


Progressively Growing GANs: Results

Conditional GANs



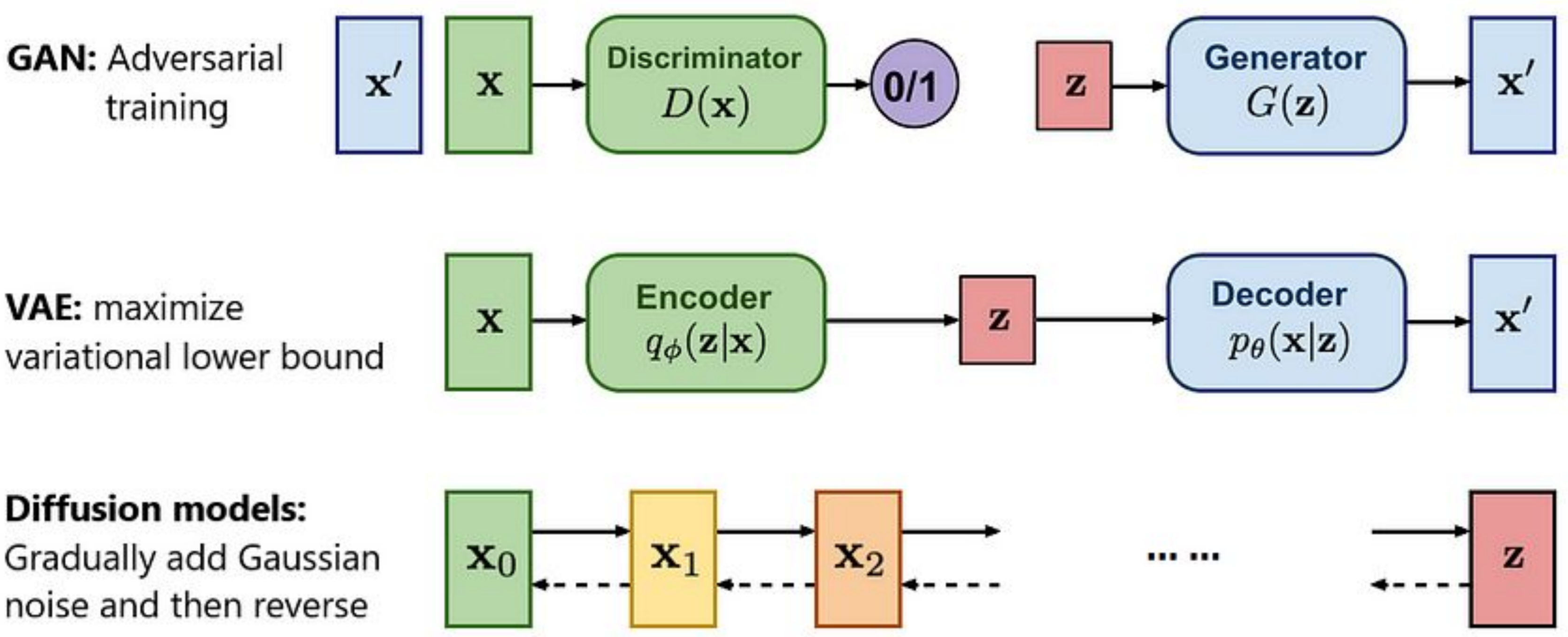
Cycle GANs



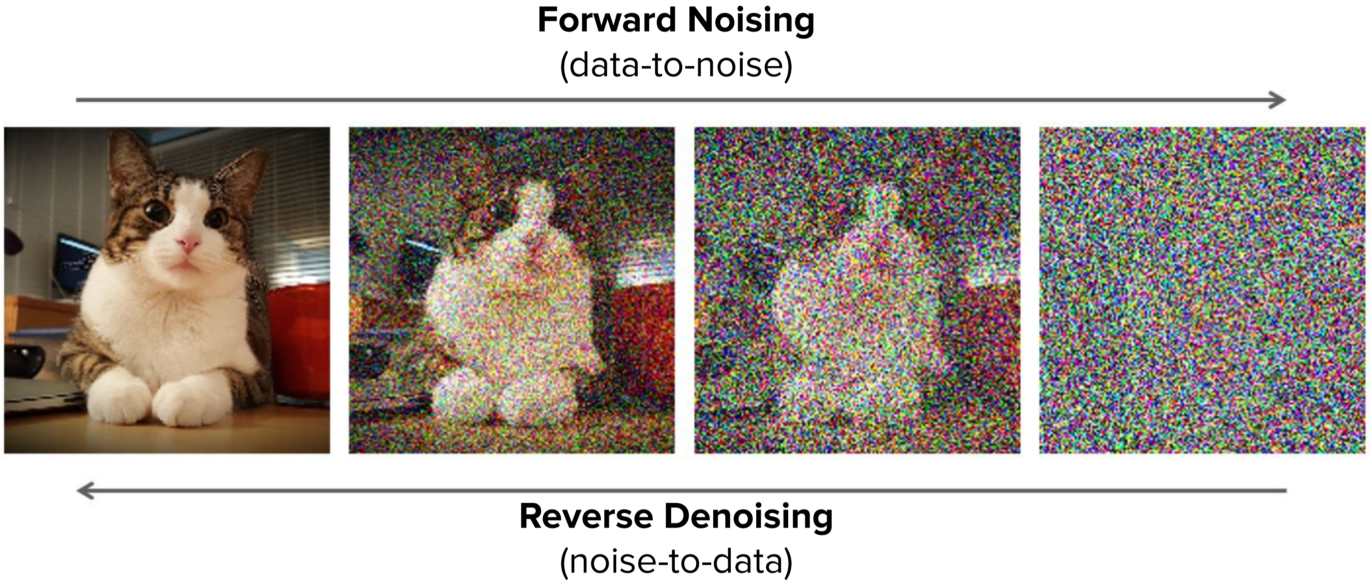
L2 Loss
G_{AB}
G_{BA}
Real Image in domain A
Fake Image in domain B
Reconstructed Image
G_{BA} generates a reconstructed image of domain A.
This makes the shape to be maintained
when G_{AB} generates a horse image from the zebra.
real or fake ?
D_B
Discriminator for domain B
Real Image in domain B

Diffusion Models!

Diffusion Models

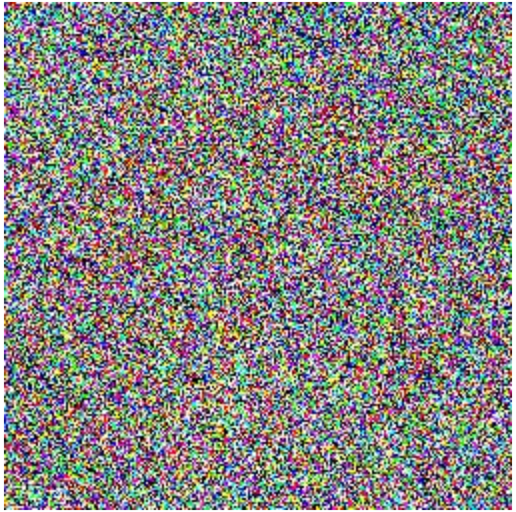


The Diffusion Process



Forward Noising

Step 1: Given an image (left), randomly sample a random noise pattern (right)



Forward Noising

Step 2: Progressively add more and more of the noise to your image

T = 0

100% Image
0% Noise

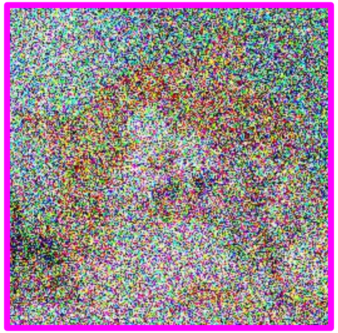
T = 1

75% Image
25% Noise

T = 2

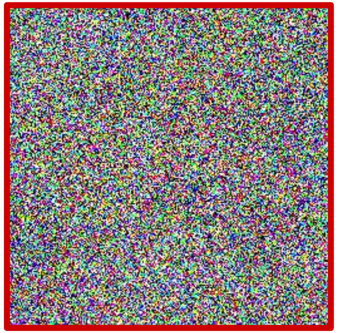
50% Image
50% Noise

T = 3



25% Image
75% Noise

T = 4



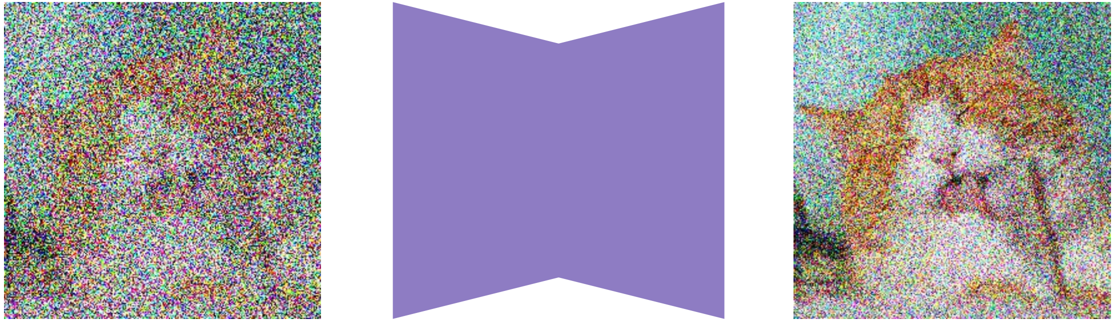
0% Image
100% Noise

Reverse Denoising

T = 0 ... T = 4

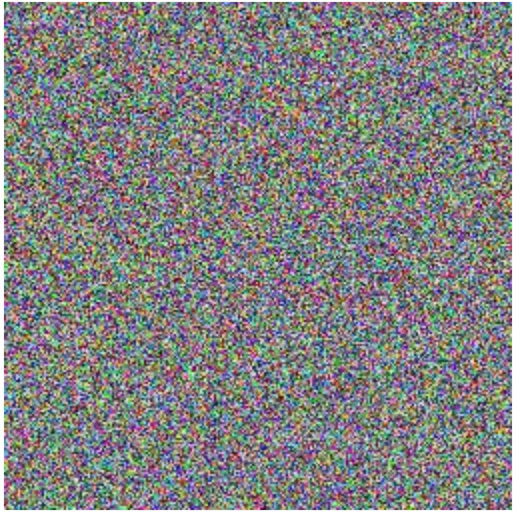
Goal: Given image at **T**, can we learn to estimate image at **T - 1**?

T = 3 **T = 2**



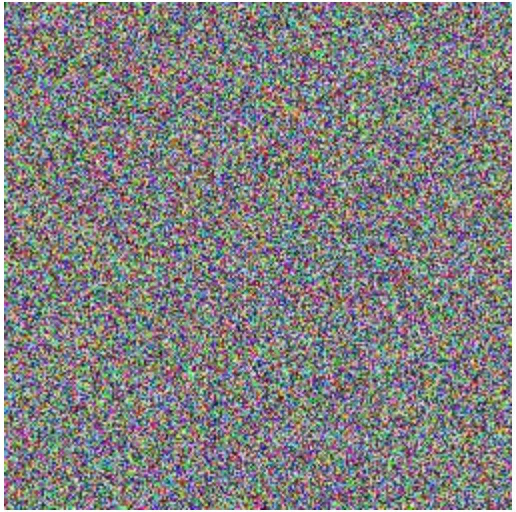
How can we train this network?

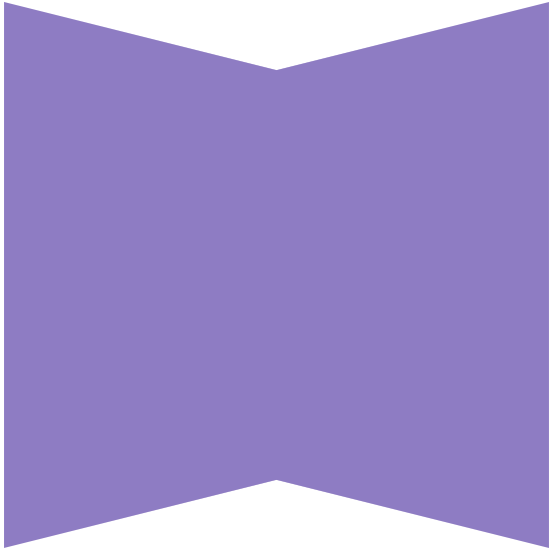
Sampling Brand New Generations

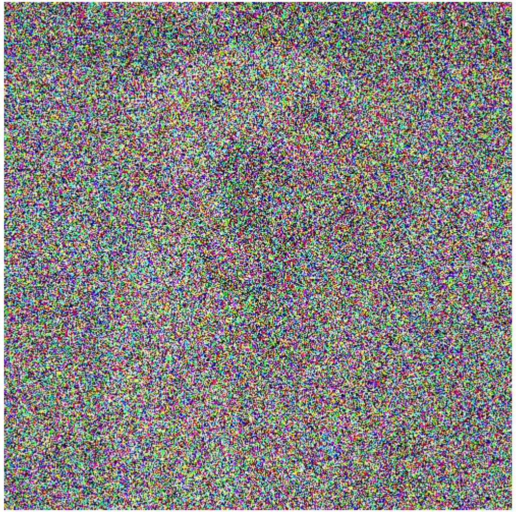


T

Sampling Brand New Generations







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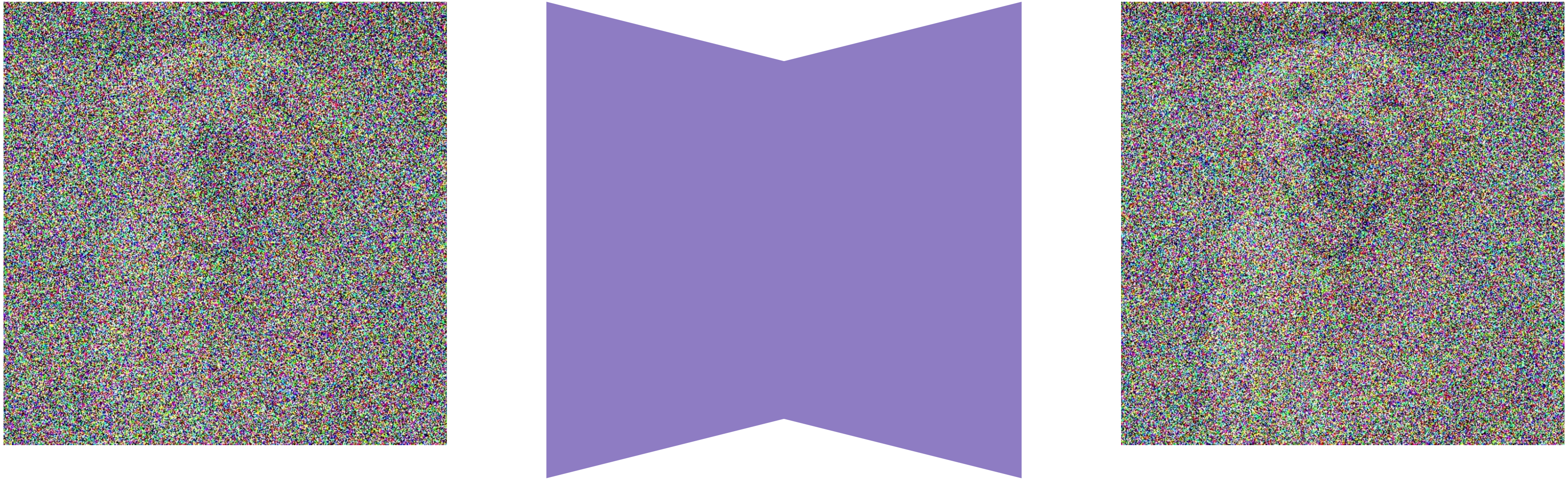

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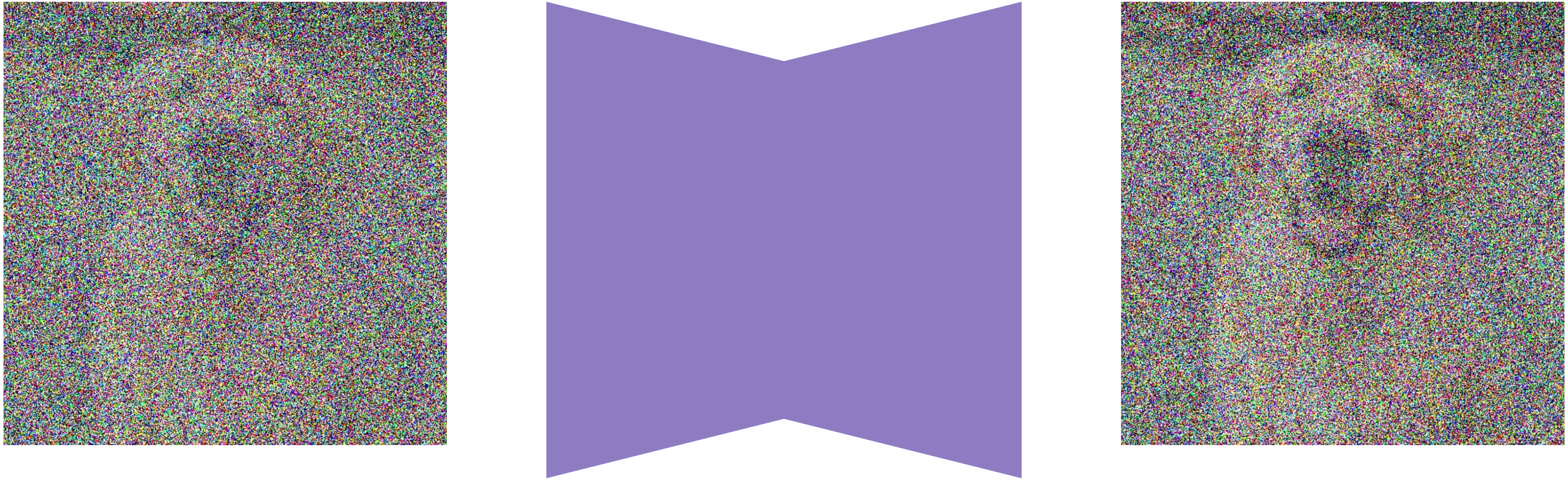

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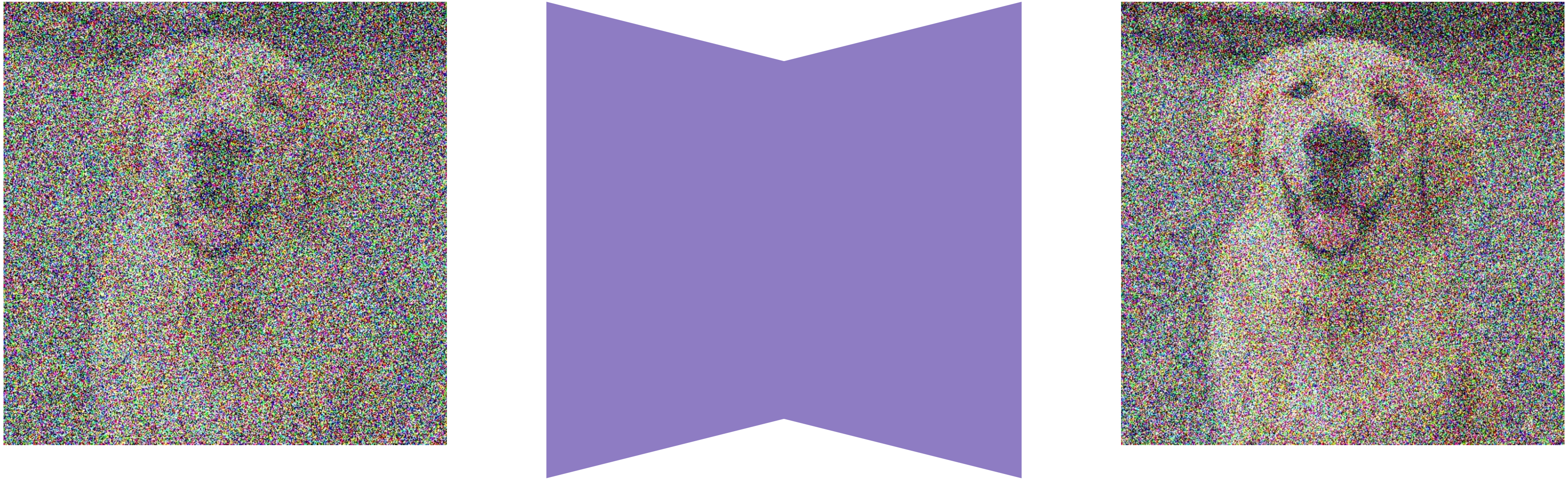

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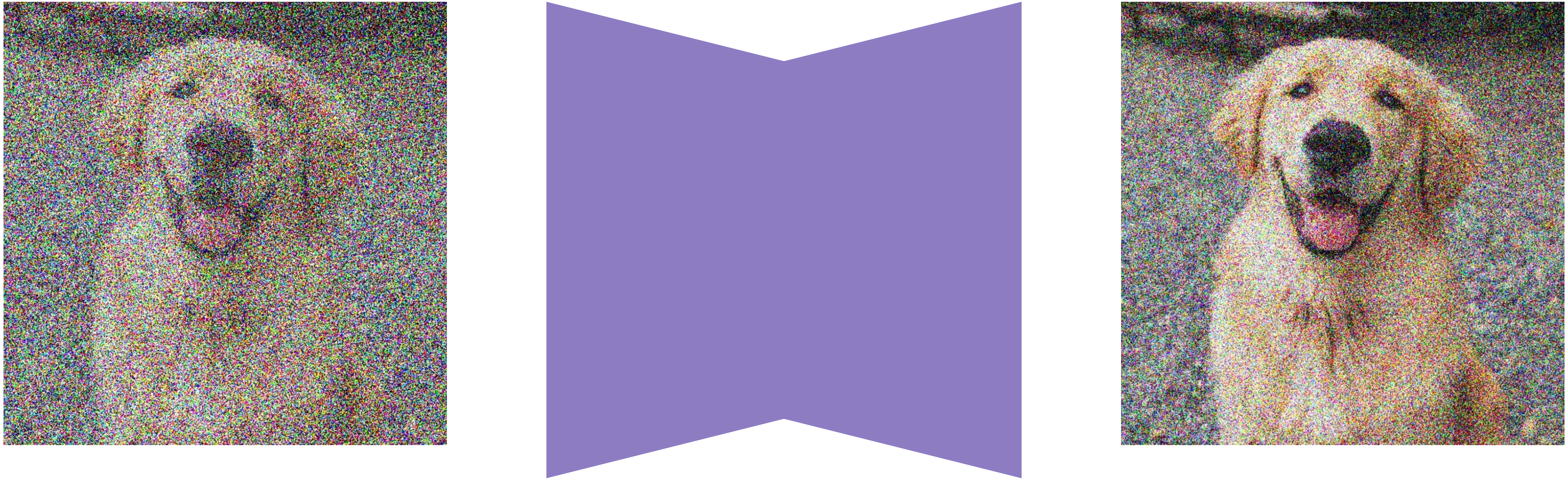

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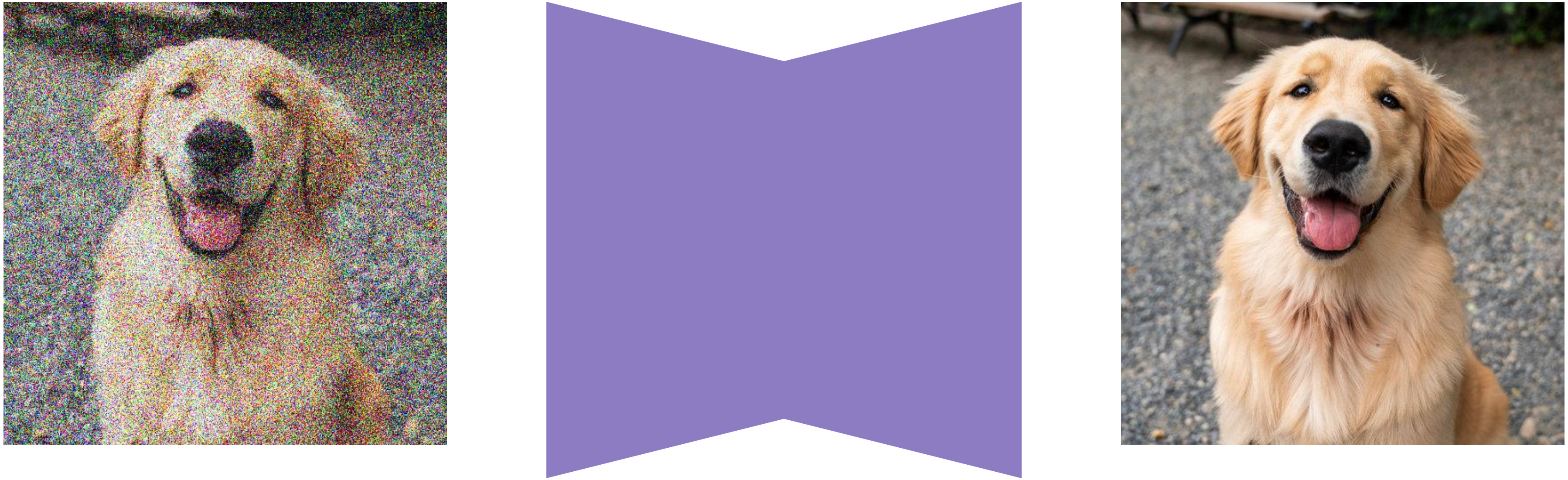

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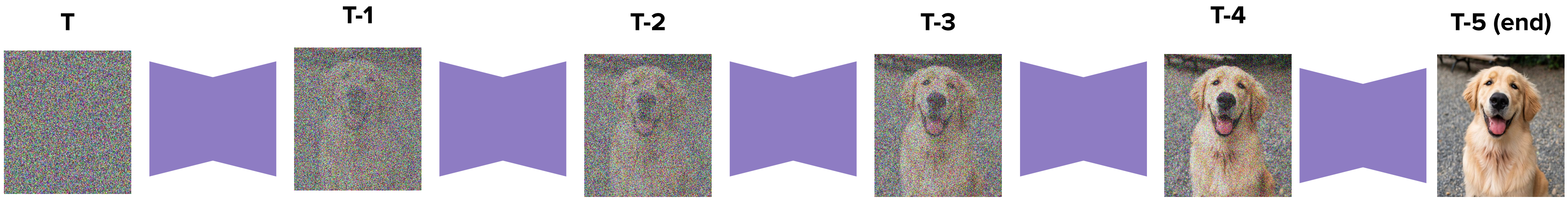
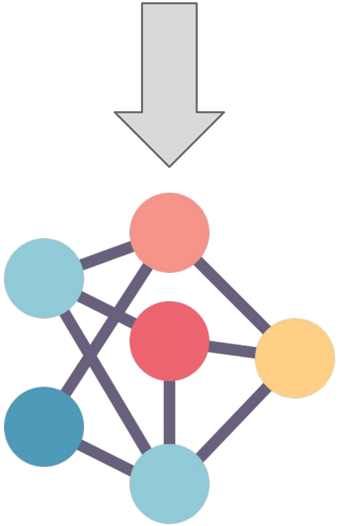


Generating Images from Natural Language

“A Photo of an astronaut riding a horse in Mars”



Generating Images from Natural Language

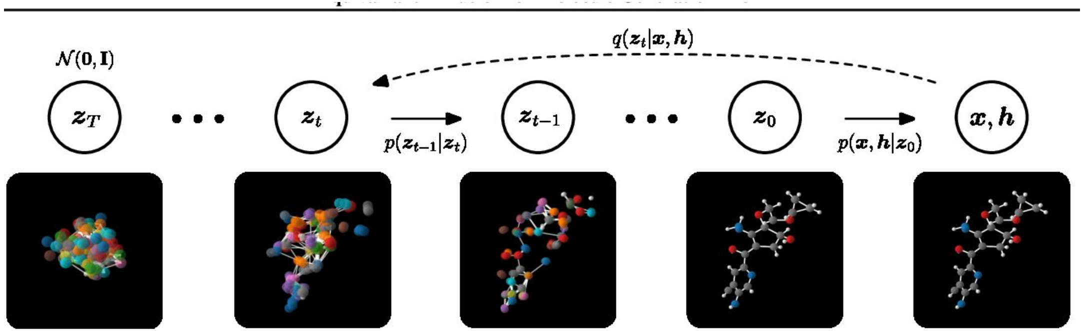
"a painting of a fox sitting in a field at sunrise in the style of Claude Monet"

"An ibis in the wild, painted in the style of John Audubon"

"close-up of a snow leopard in the snow hunting, rack focus, nature photography"

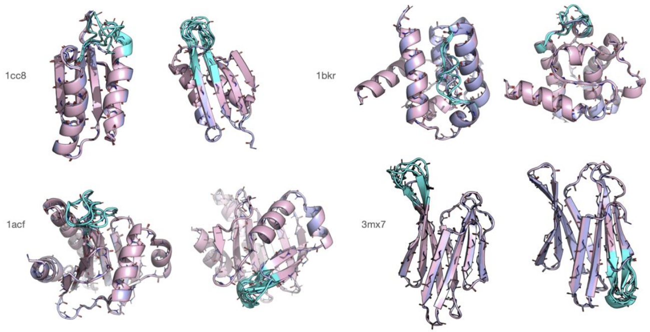
Beyond Images: Molecular Design

Chemistry: Generating Molecules in 3D



Equivariant Diffusion for Molecule Generation in 3D

Biology: Generating Novel Proteins



Protein Structure and Sequence Generation with Equivariant Denoising Diffusion Probabilistic Models

Next Lecture: Object Detection And Segmentation!