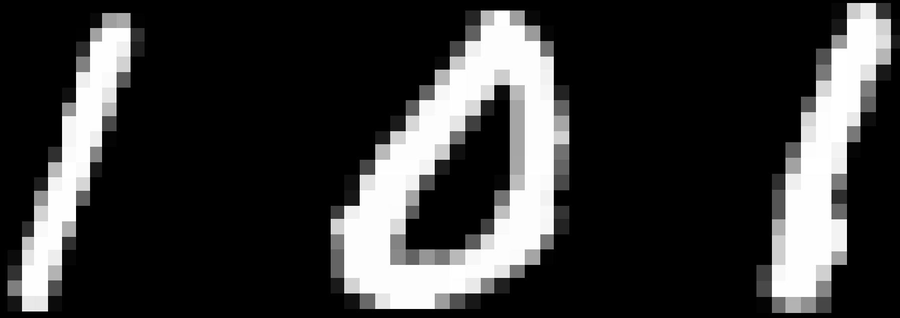
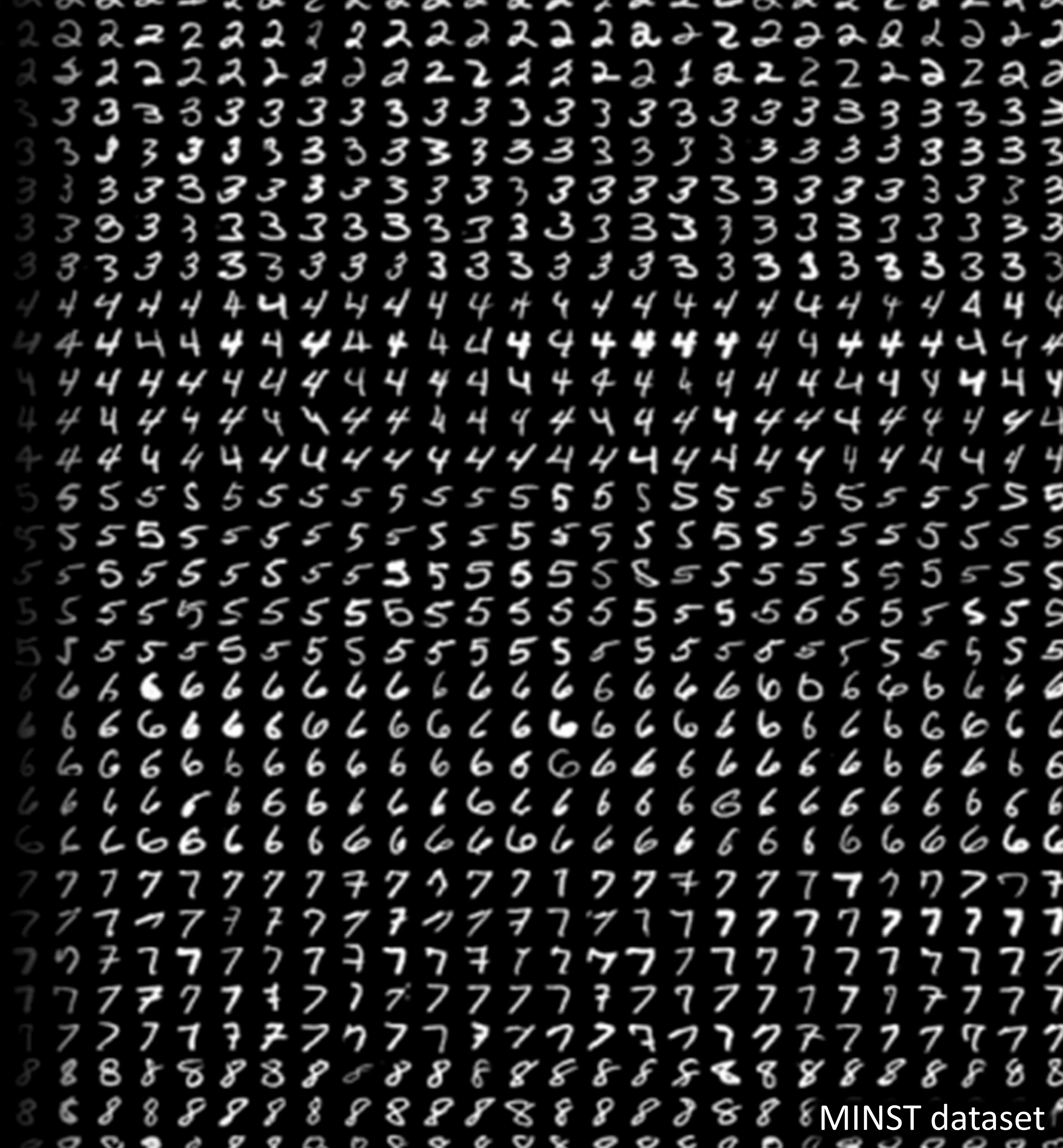
GAN





MINST dataset

Andrei Kazantsev
Max Planck Institute for Radio Astronomy

Generative **A**dversarial **N**etworks

Human Neuron Researches

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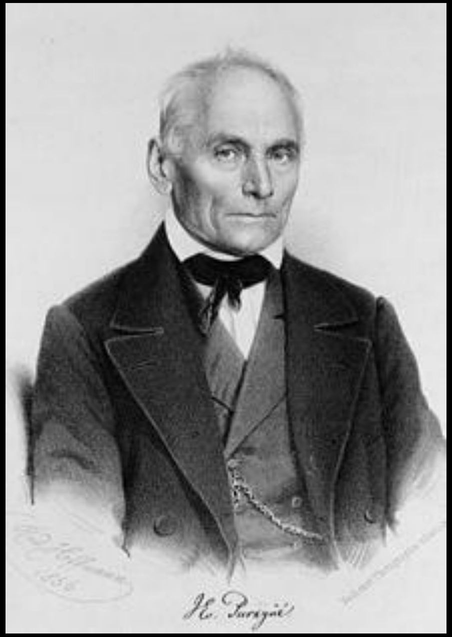
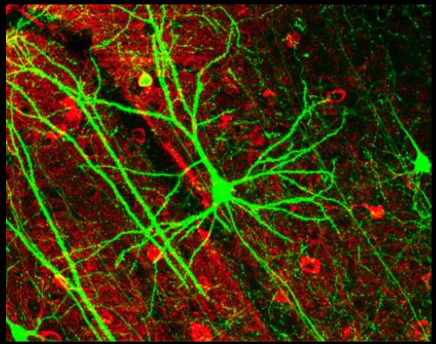


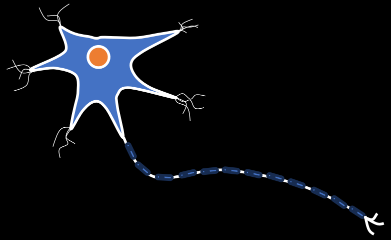
Jan Evangelista Purkyně
(1787 – 1869)

Camillo Golgi
(1843 – 1926)

Santiago Ramón y Cajal
(1852 – 1934)

Nobel Prize in Physiology or Medicine 1906
"*in recognition of their work on the structure of the nervous system*"





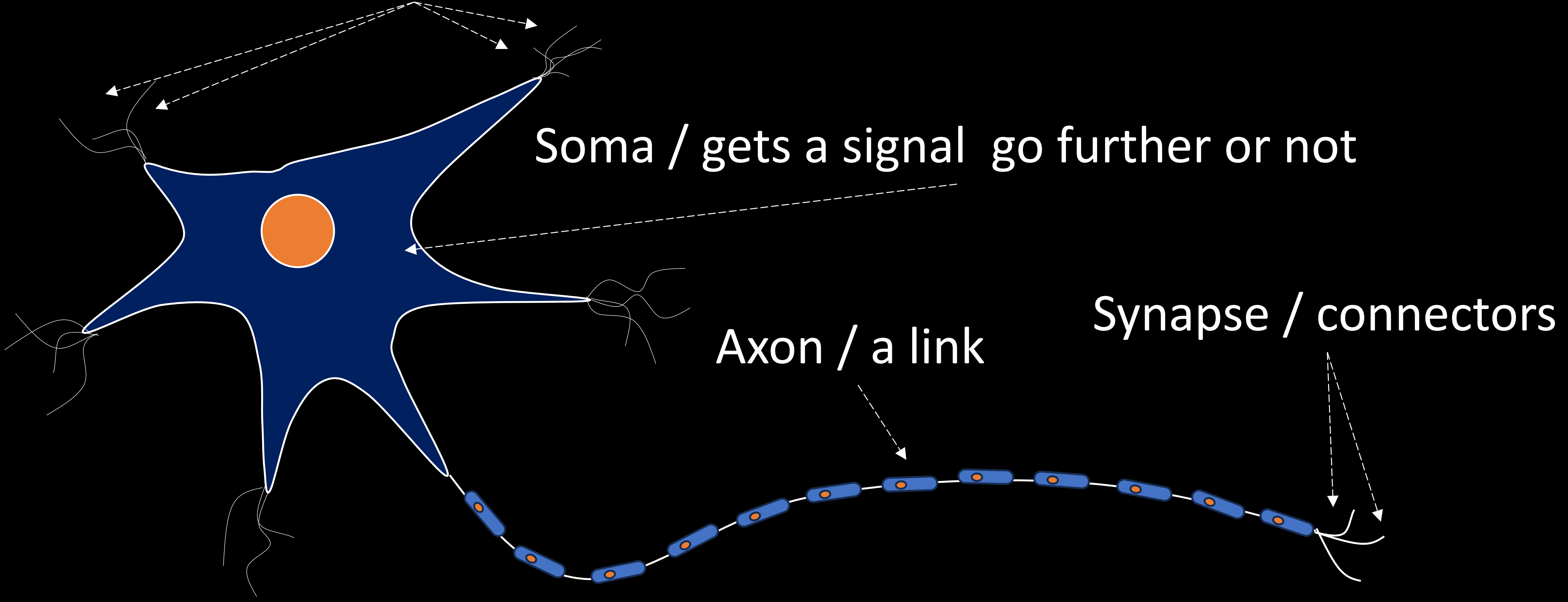
1837

1873

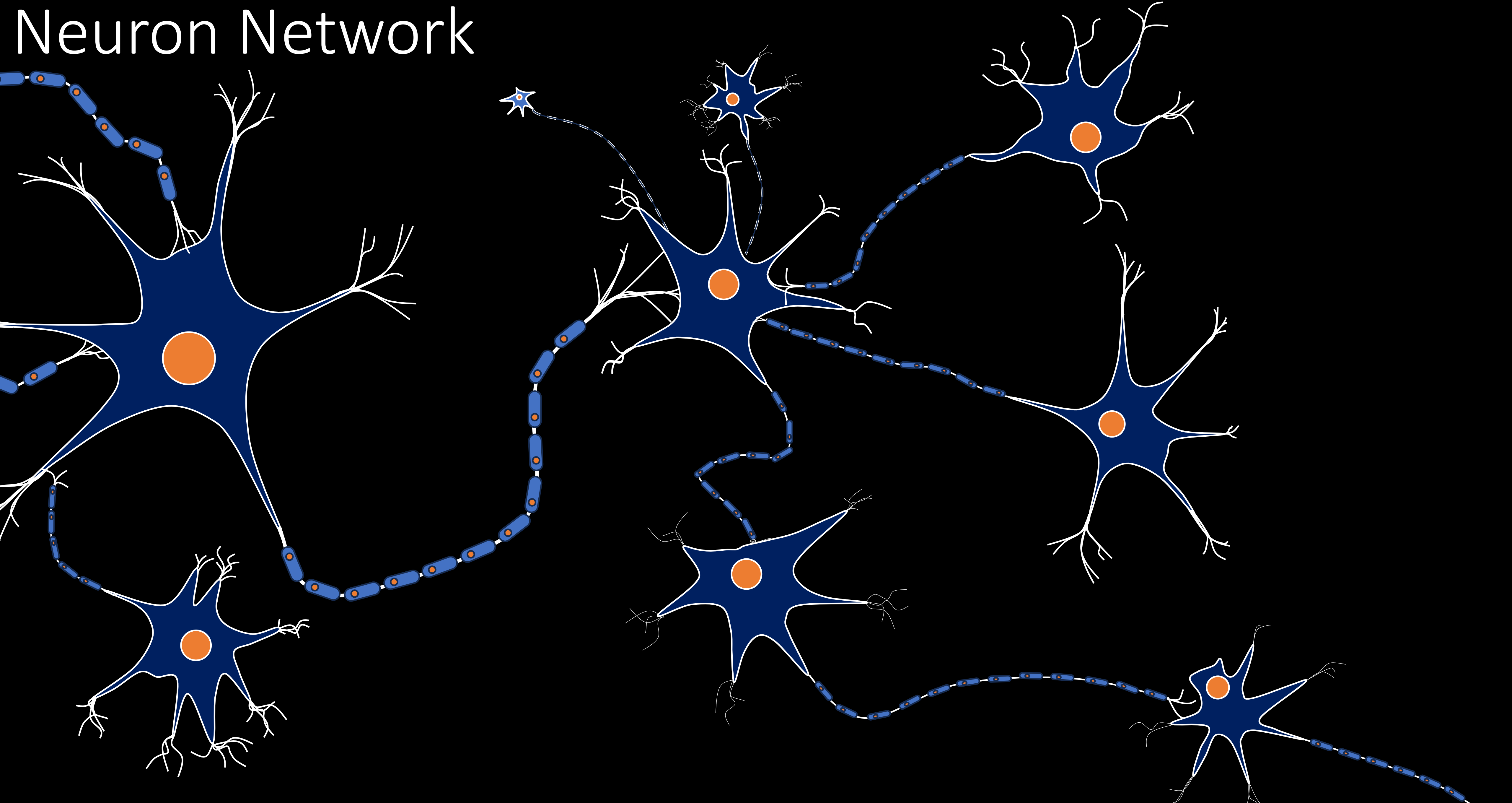
1891

Neuron

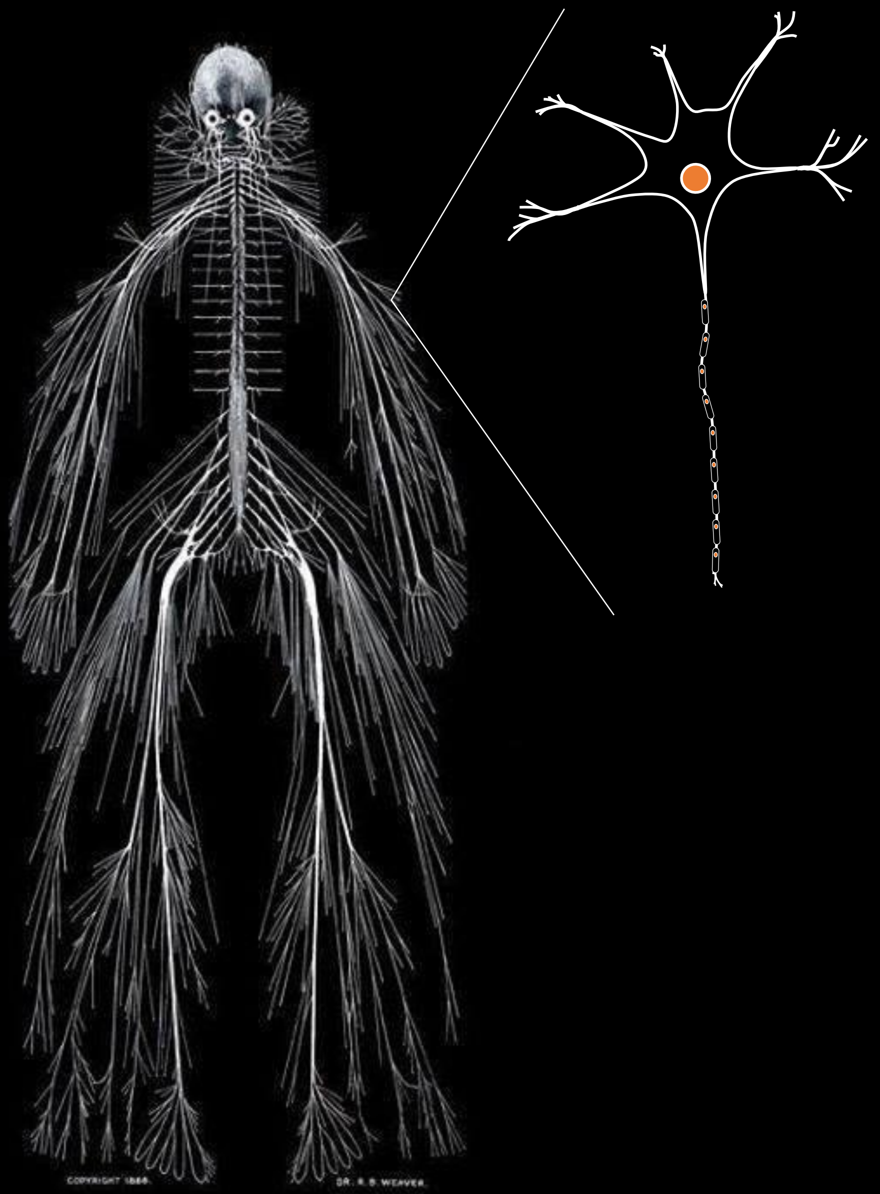
Dendrites / (and a whole body, actually) receive a signal



Neuron Network



Human nervous system



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Neurons are the fundamental structural and functional units of the **nervous system**.

The entire human brain contains 86 billion neurons

Neurons perform three main functions:

1. **Sensory function (afferent neurons)**
2. **Integrative function (interneurons)**
3. **Motor function (efferent neurons)**

Mathematical Neuron

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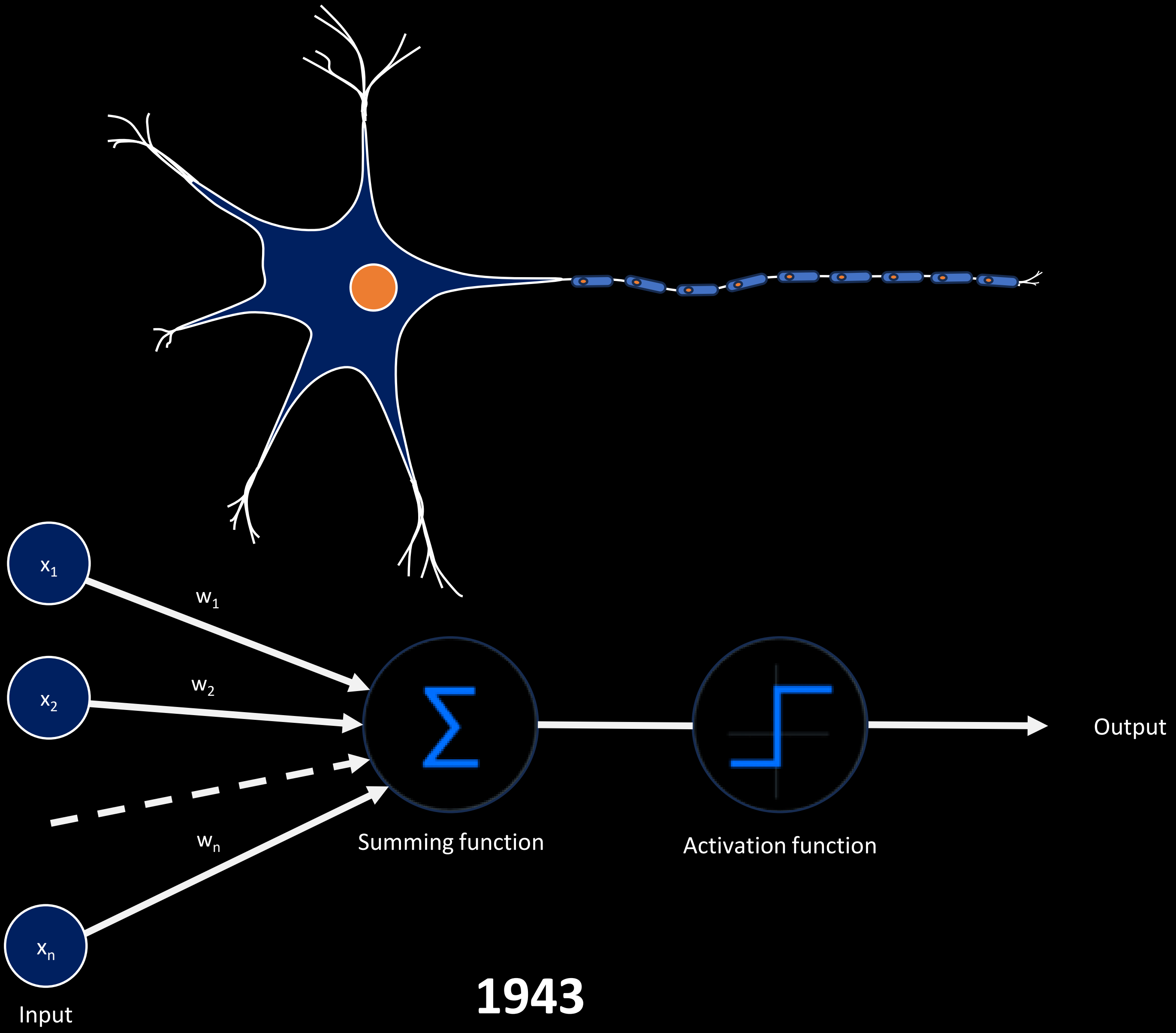
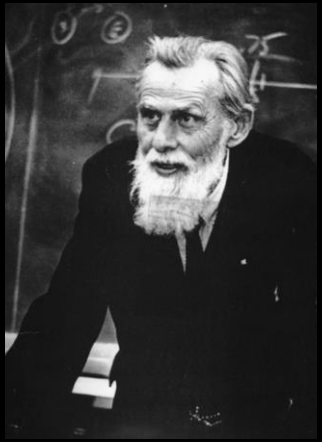
Walter Pitts
(1923 – 1969)





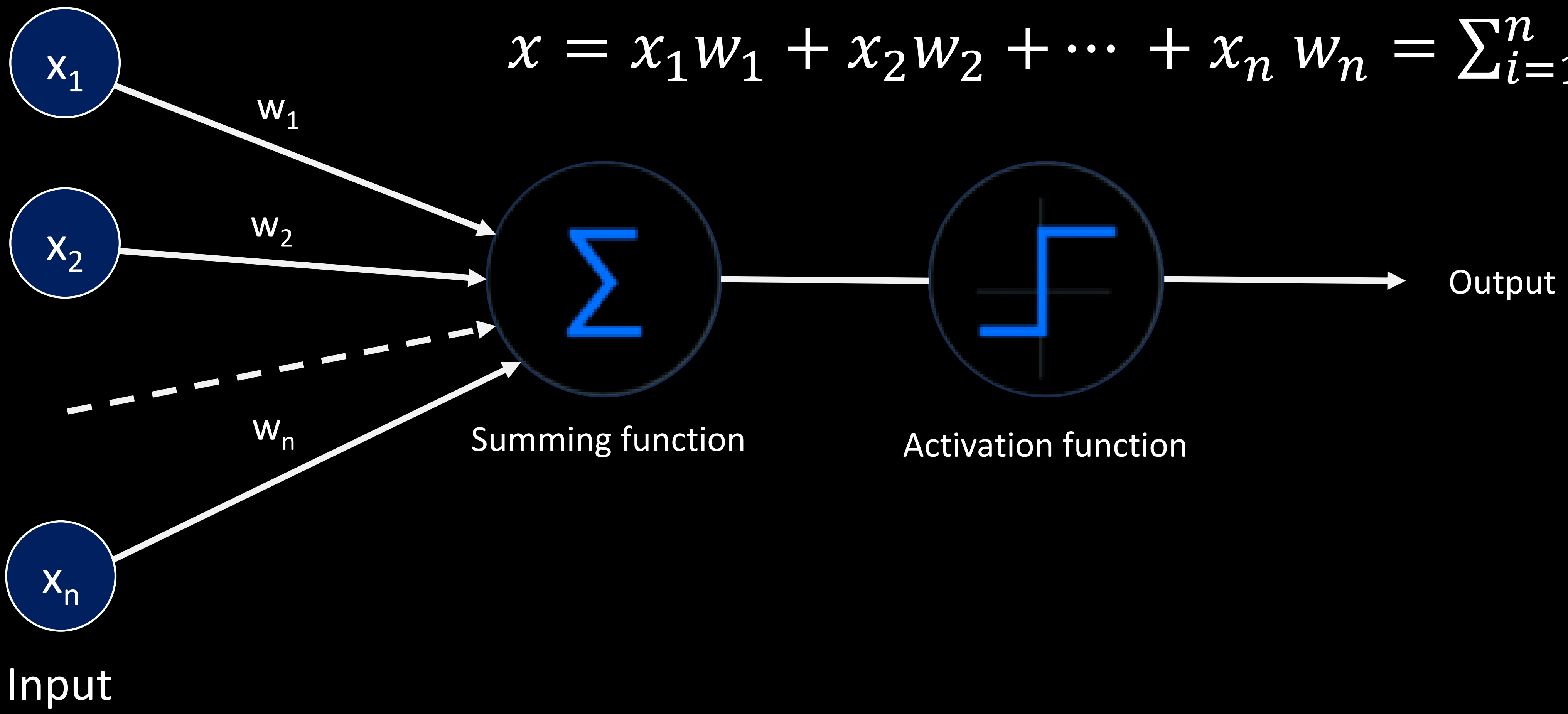
Warren Sturgis
McCulloch
(1898 – 1969)

1943

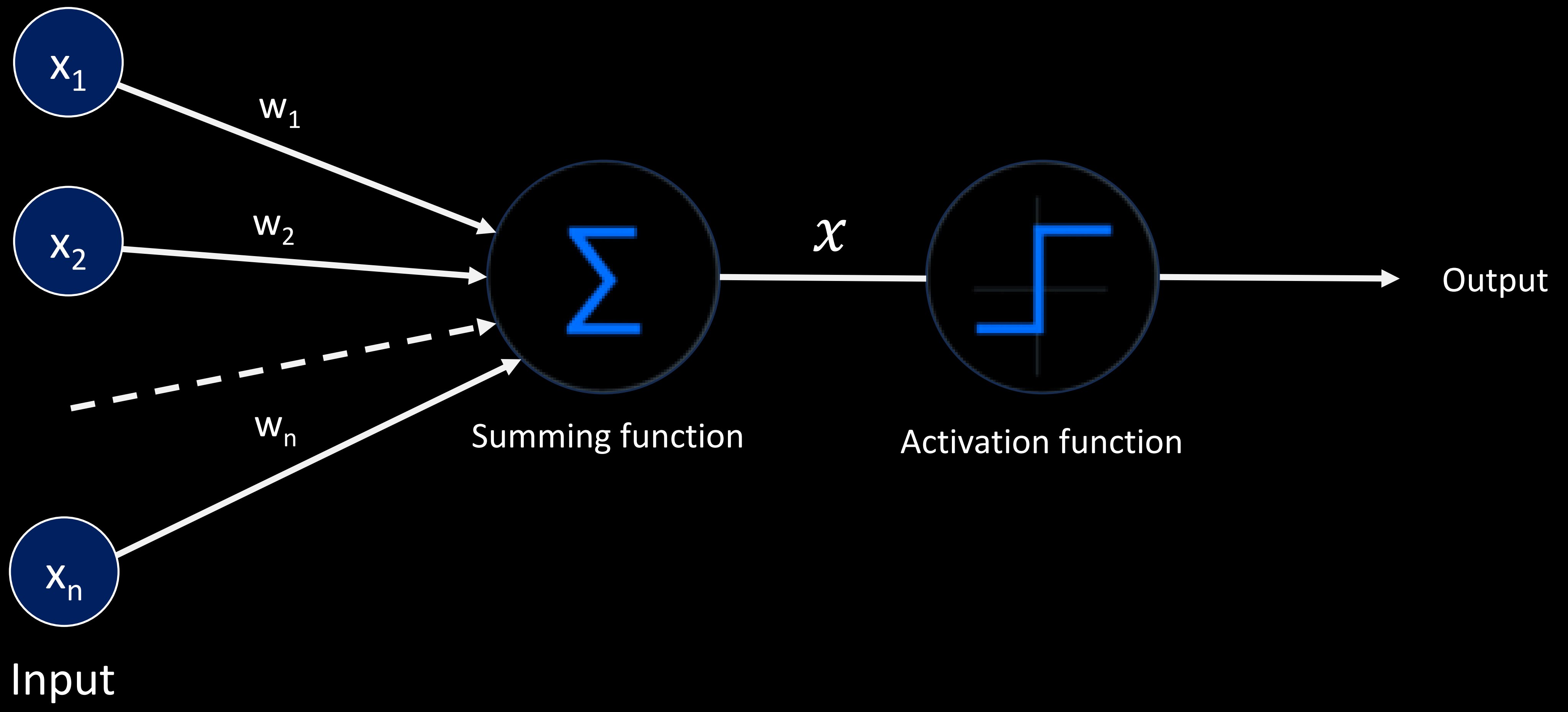
McCulloch, W.S., Pitts, W. A logical calculus of the ideas immanent in nervous activity. *Bulletin of Mathematical Biophysics* **5**, 115–133 (1943). https://doi.org/10.1007/BF02478259

Mathematical Neuron

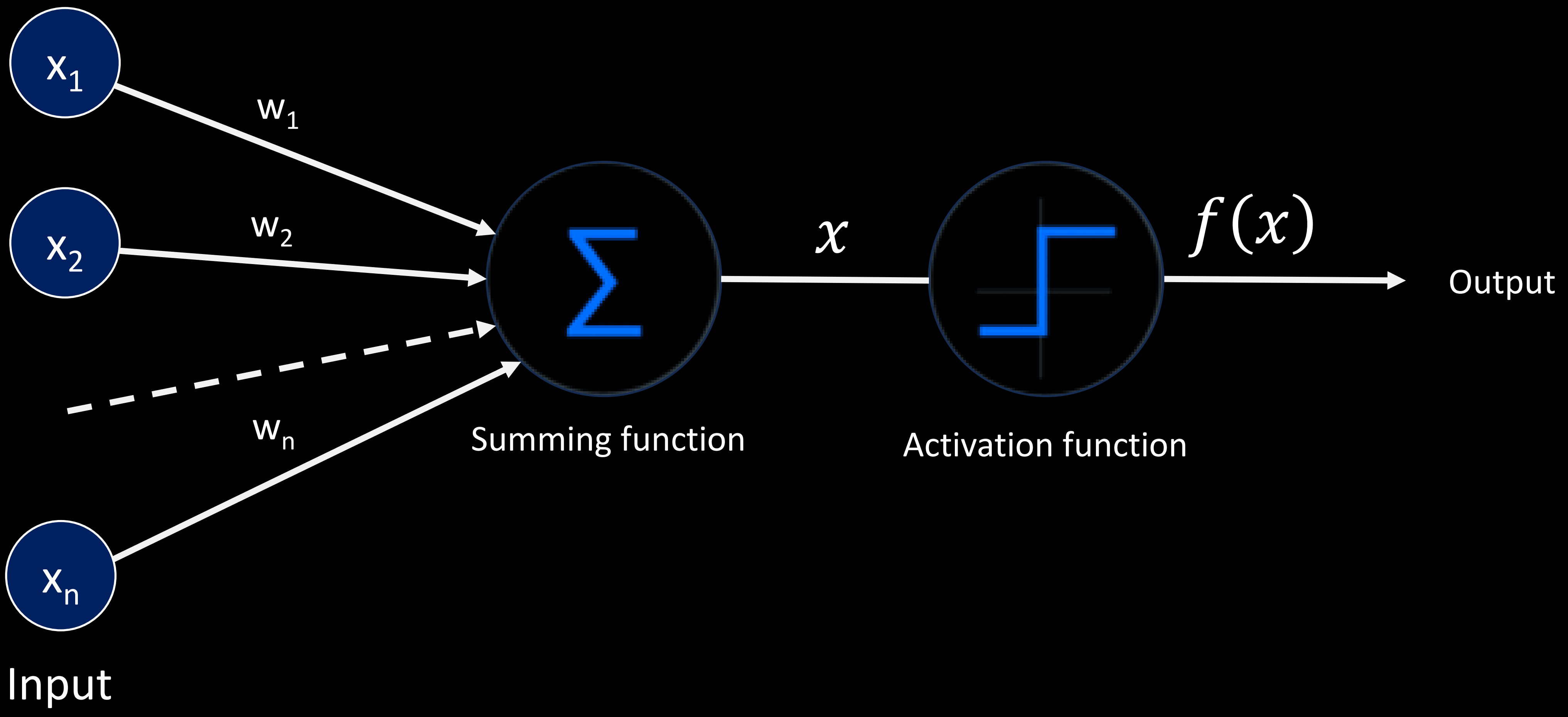
$$x = x_1 w_1 + x_2 w_2 + \cdots + x_n\, w_n = \sum_{i=1}^{n} x_i w_i$$



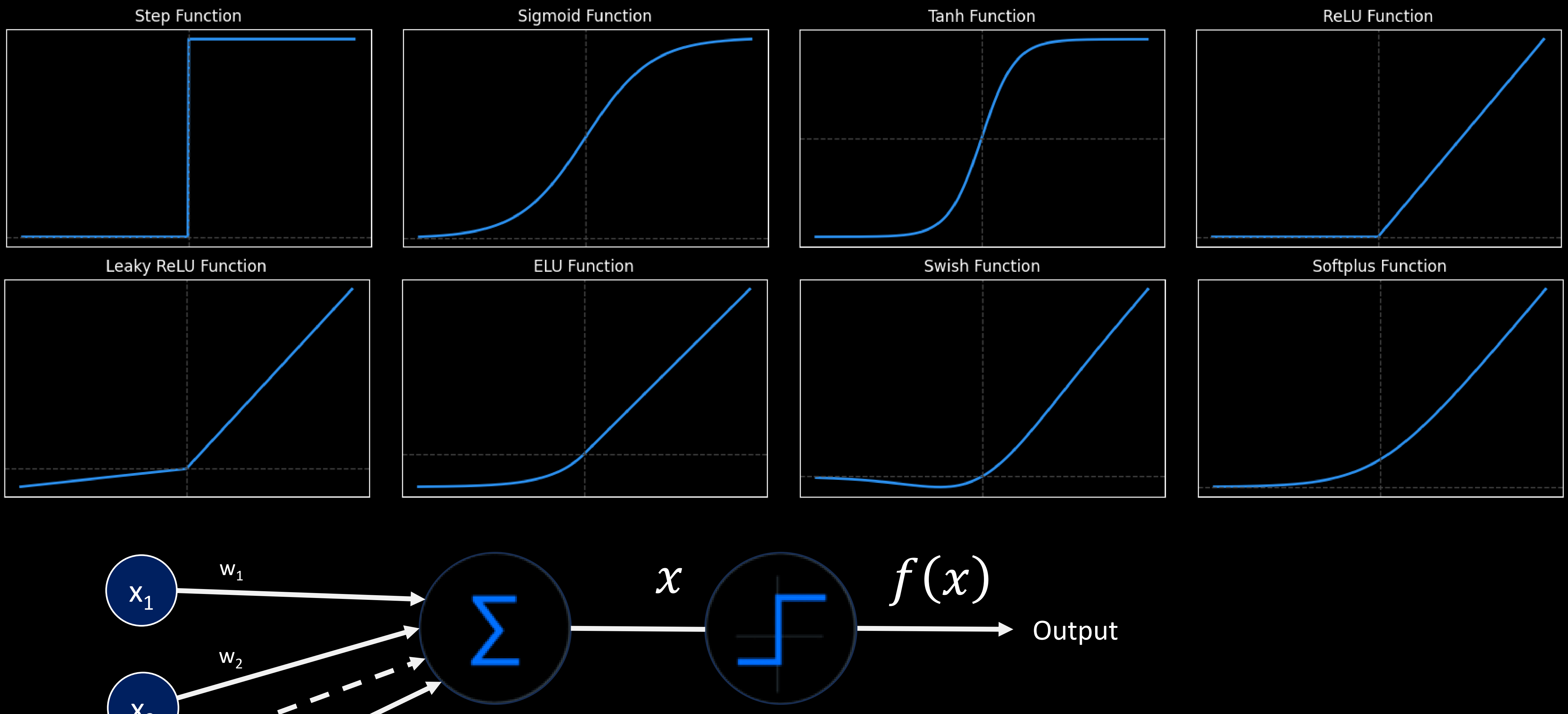
Mathematical Neuron



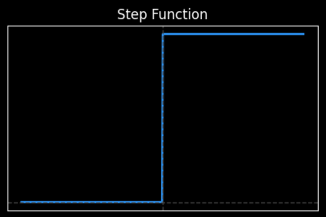
Mathematical Neuron



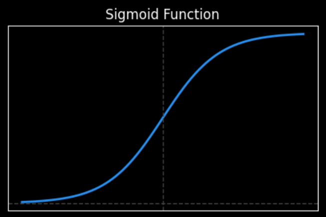
Activation Functions



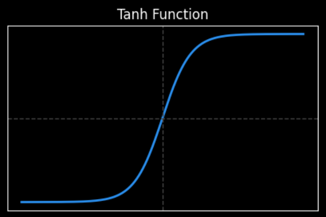
Activation Functions



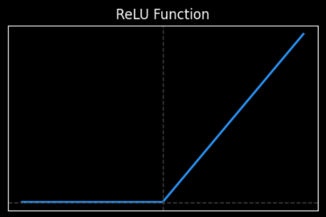
$$f(x) = \begin{cases} 1, x \geq 0 \\ 0, x < 0 \end{cases}$$



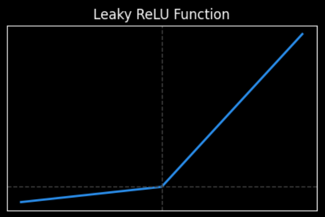
$$f(x) = \frac{1}{1 + e^{-x}}$$



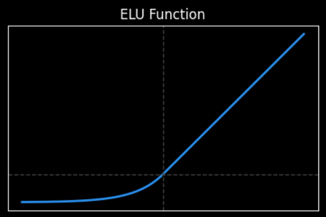
$$f(x) = \tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$$



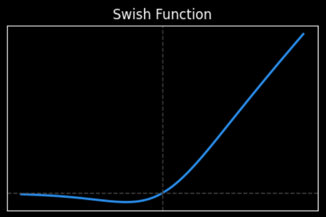
$$f(x) = \max(0, x)$$



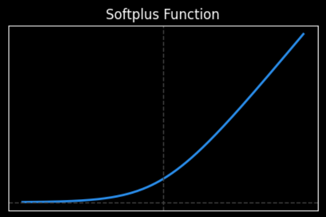
$$f(x) = \begin{cases} x, x \geq 0 \\ ax, x < 0 \end{cases}$$



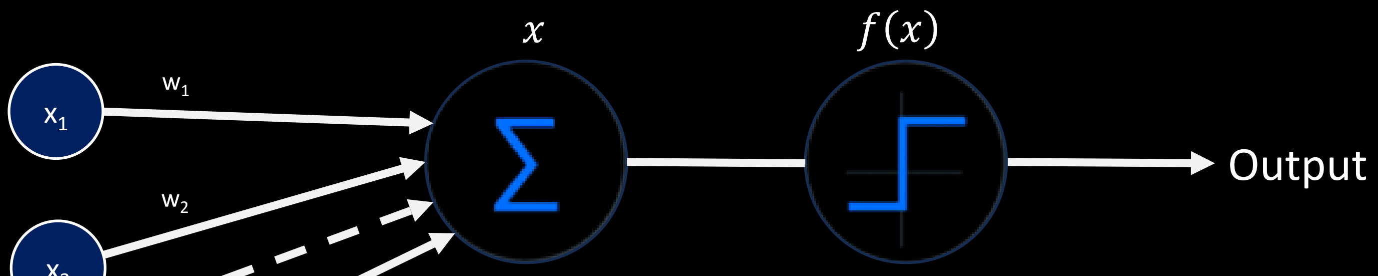
$$f(x) = \begin{cases} x, & x \geq 0 \\ a(e^x - 1), & x < 0 \end{cases}$$



$$f(x) = x \frac{1}{1 + e^{-x}}$$



$$f(x) = \log(1 + e^x)$$



Training of a Perceptron

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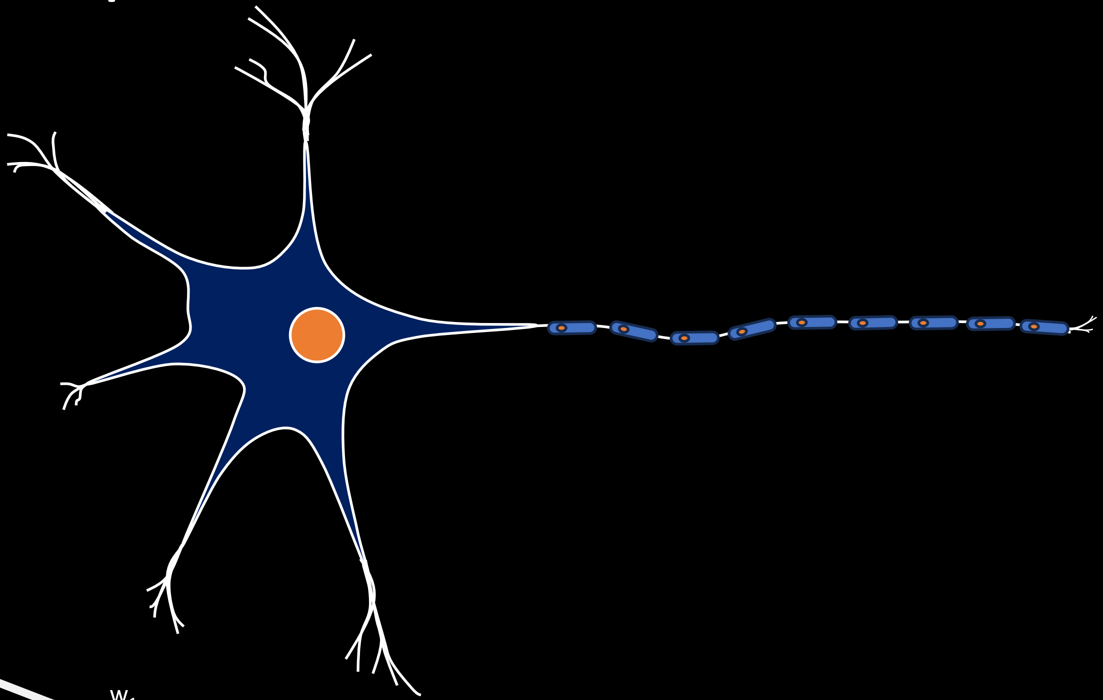
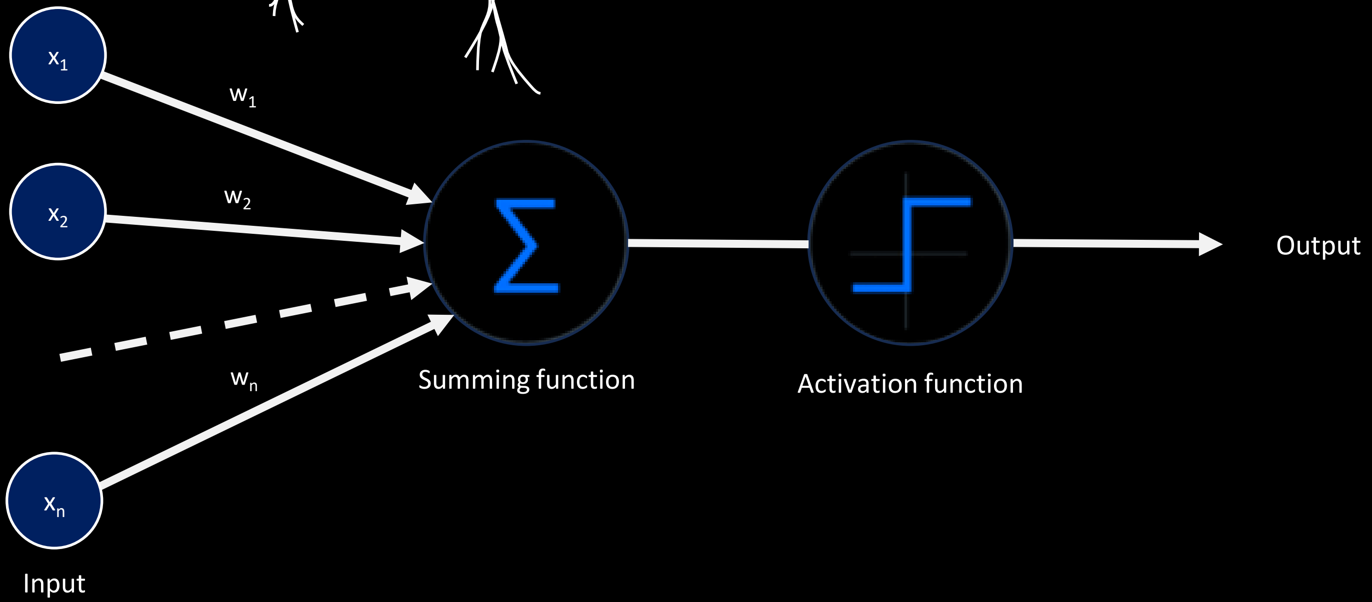
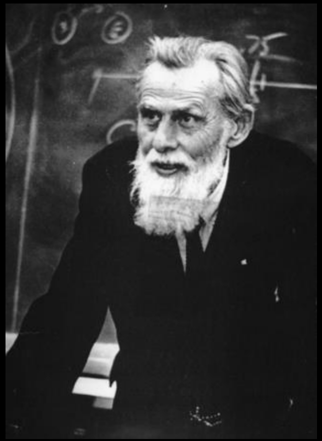
Walter Pitts
(1923 – 1969)





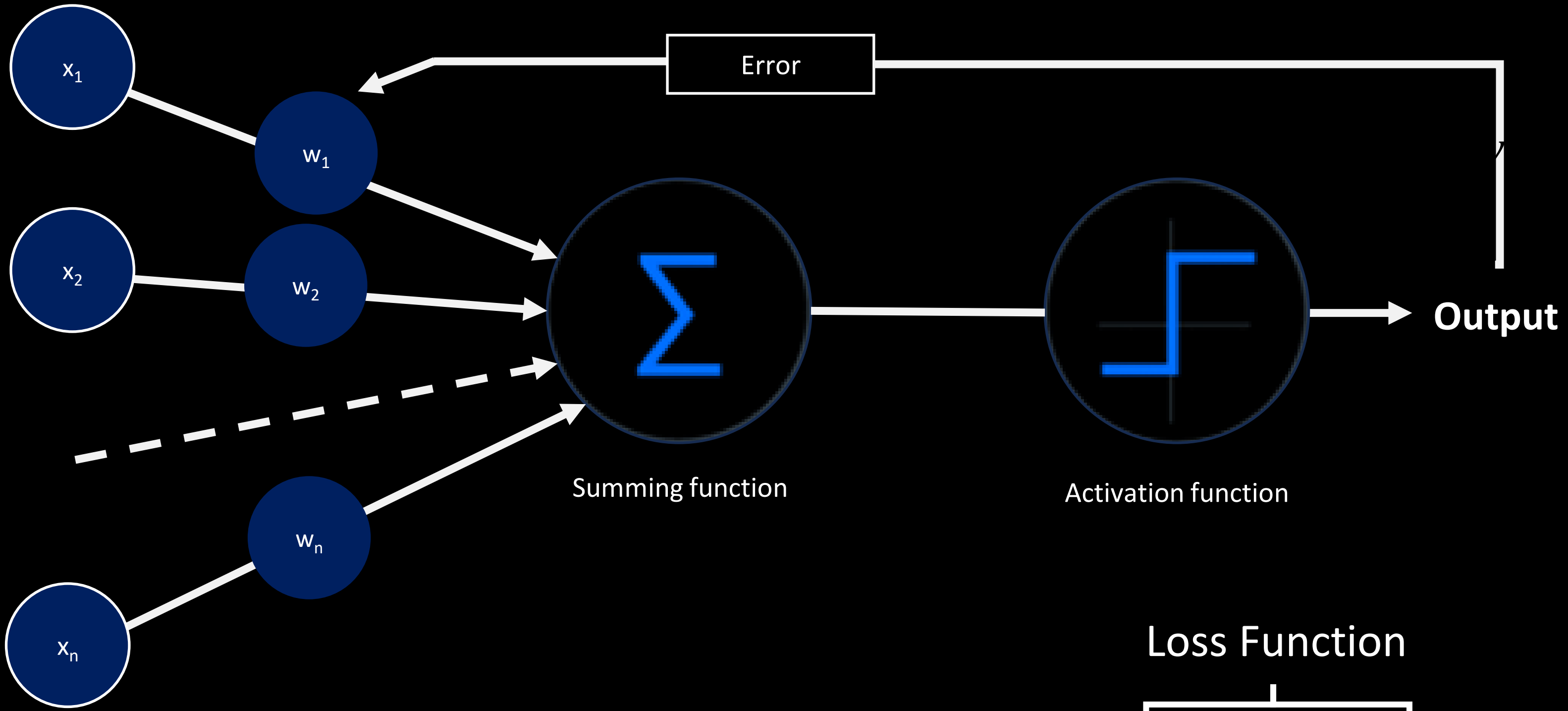


Warren Sturgis
McCulloch
(1898 – 1969)

McCulloch, W.S., Pitts, W. A logical calculus of the ideas immanent in nervous activity. *Bulletin of Mathematical Biophysics* **5**, 115–133 (1943). https://doi.org/10.1007/BF02478259

Training of a Perceptron via Gradient Descent of Loss Function

Frank Rosenblatt
(1928 – 1971)

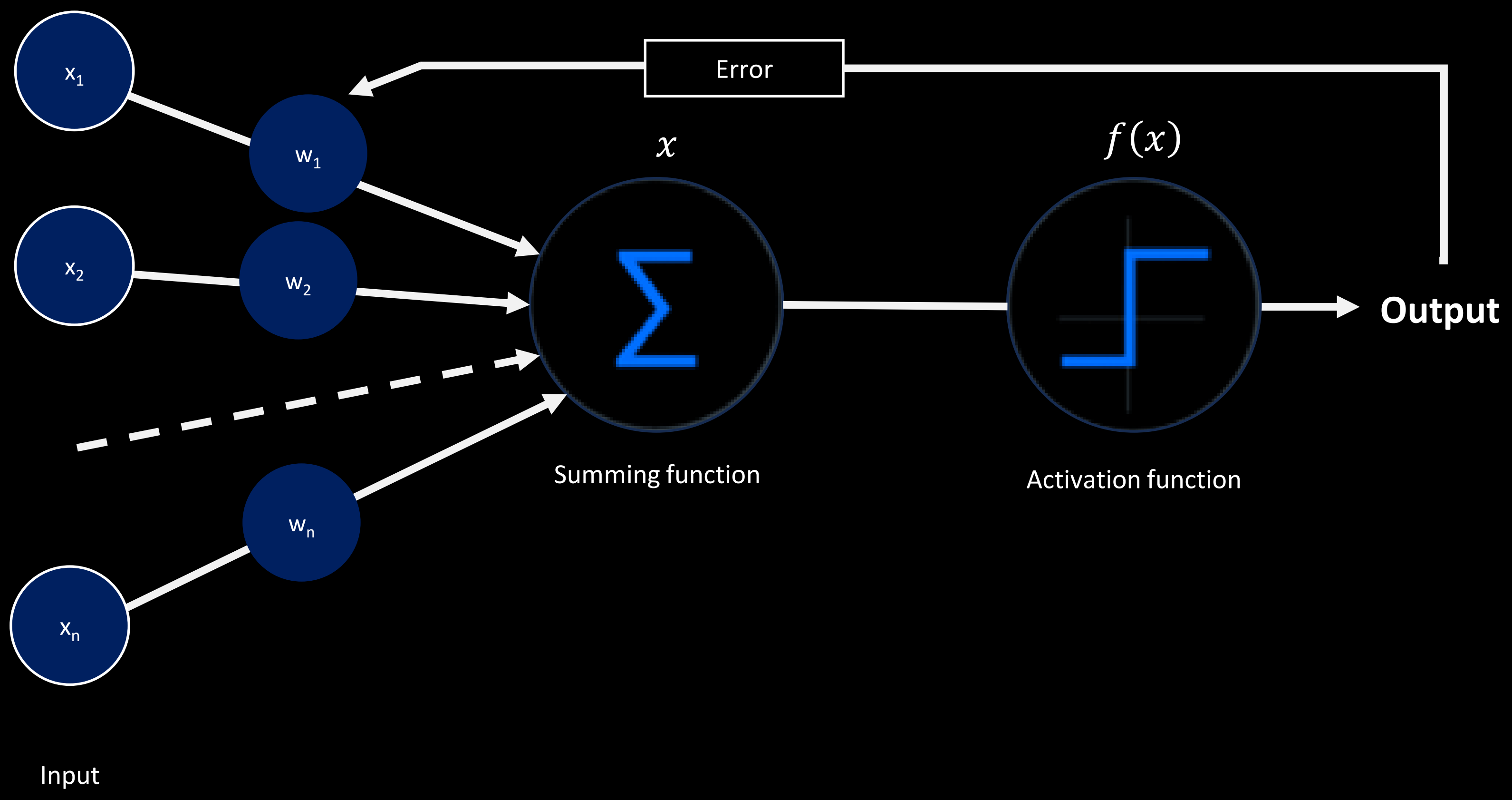


$$w_{new} = w_{old} - \underbrace{\varepsilon}_{\text{Learning rate}} \cdot \overbrace{\nabla L(w_{old})}^{\text{Loss Function}}$$

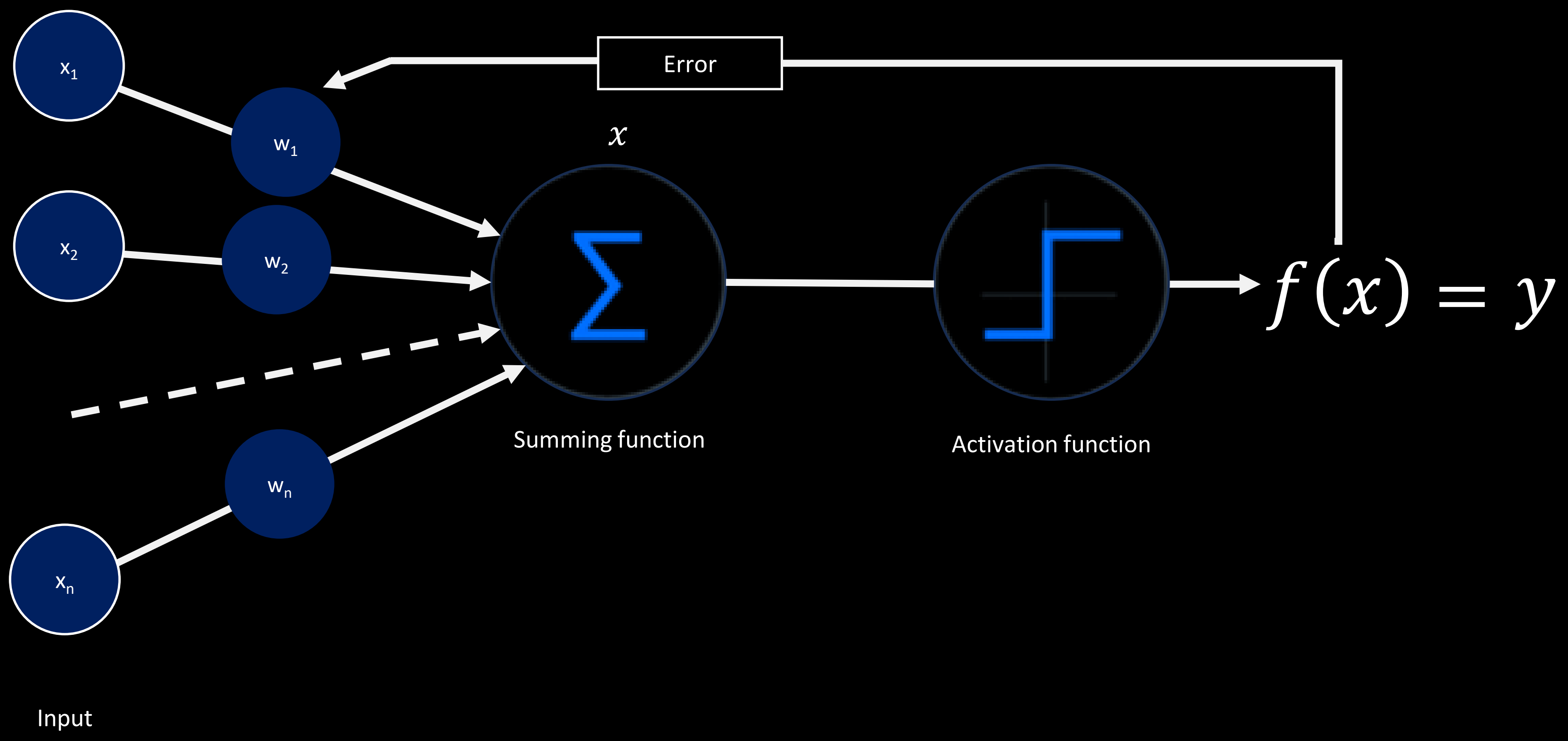
1958

Rosenblatt, F. (1958). *"The perceptron: A probabilistic model for information storage and organization in the brain". Psychological Review.* ***65*** *(6): 386–408. doi:10.1037/h0042519.*

Loss Function



Loss Function



Loss Function

We received from the perceptron

$$y \qquad\qquad \hat{y}$$

We were expecting to receive

Loss Function

We received from the perceptron

Error

$$y - \hat{y}$$

We were expecting to receive

Loss Function

$$L(y, \hat{y}) = y - \hat{y}$$

Loss Function

$$L(y,\hat{y}) = \frac{(y-\hat{y})^2}{2}$$

Loss Function

$$L(y, \hat{y}) = E_{\hat{x}\sim P_g}[D(\hat{x})] - E_{x\sim P_r}[D(x)] + \\ +\lambda E_{x\sim P_r}[(\|\nabla_{\tilde{x}} D(\tilde{x})\|_2 - 1)^2]$$

Loss Function

$$L(y, \hat{y}) = E_{\hat{x} \sim P_g}[D(\hat{x})] - E_{x \sim P_r}[D(x)] + \\ +\lambda E_{x \sim P_r}[(\|\nabla_{\tilde{x}} D(\tilde{x})\|_2 - 1)^2]$$

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Loss Function

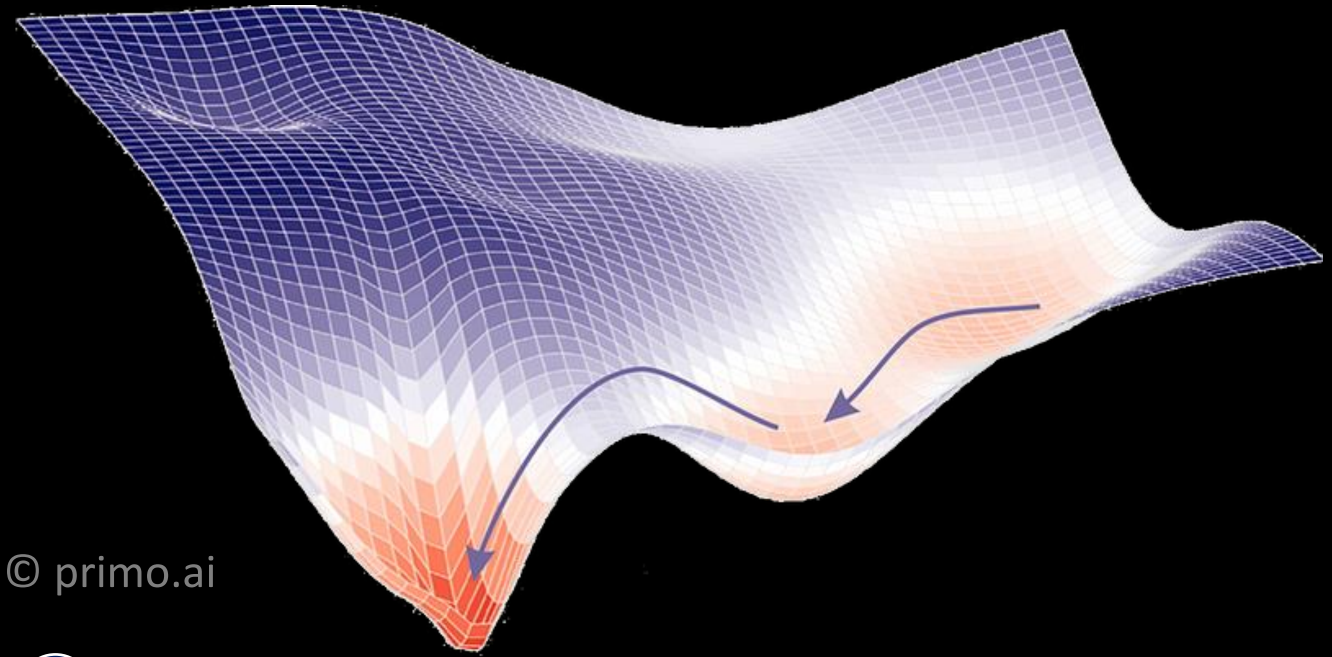
$$L(y, \hat{y}) = \frac{(y - \hat{y})^2}{2}$$

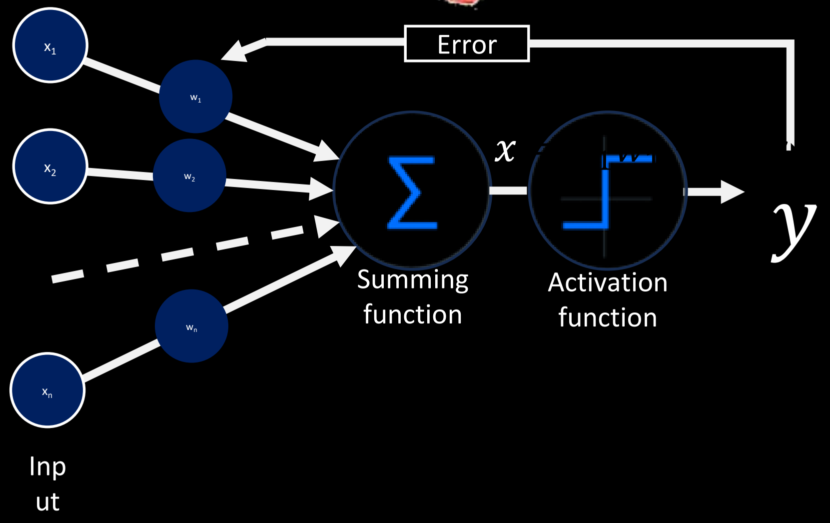
Gradient Descent of Loss Function and New Weights

$$L(y,\hat{y}) = \frac{(y-\hat{y})^2}{2}$$

$$\nabla f = \left(\frac{\partial f}{\partial x_1}, \frac{\partial f}{\partial x_2} \dots, \frac{\partial f}{\partial x_n}\right)$$

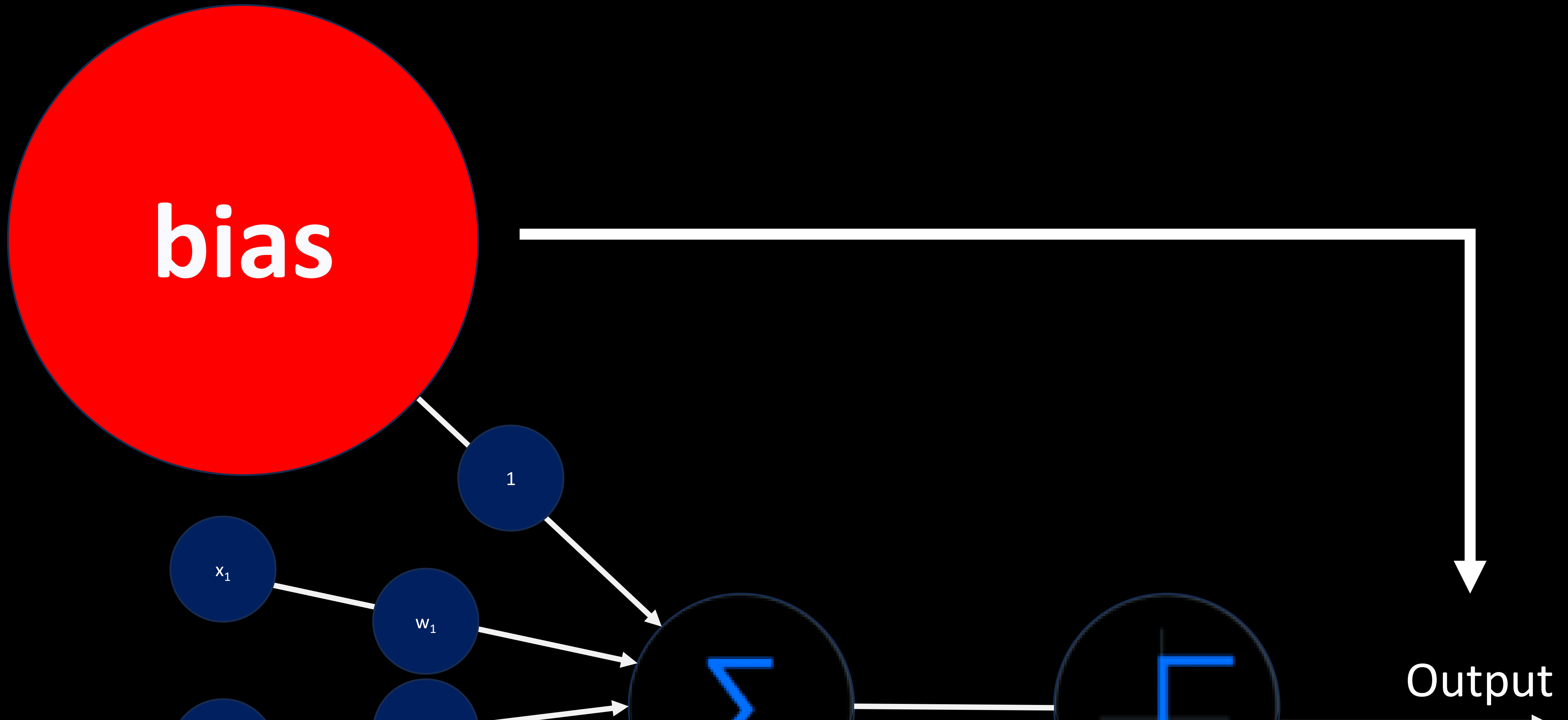
$$\nabla L = \frac{\partial L}{\partial w} = \underbrace{\frac{\partial L}{\partial y}}_{(y-\hat{y})} \cdot \underbrace{\frac{\partial y}{\partial (w \cdot x)}}_{1} \cdot \underbrace{\frac{\partial (w \cdot x)}{\partial w}}_{x}$$



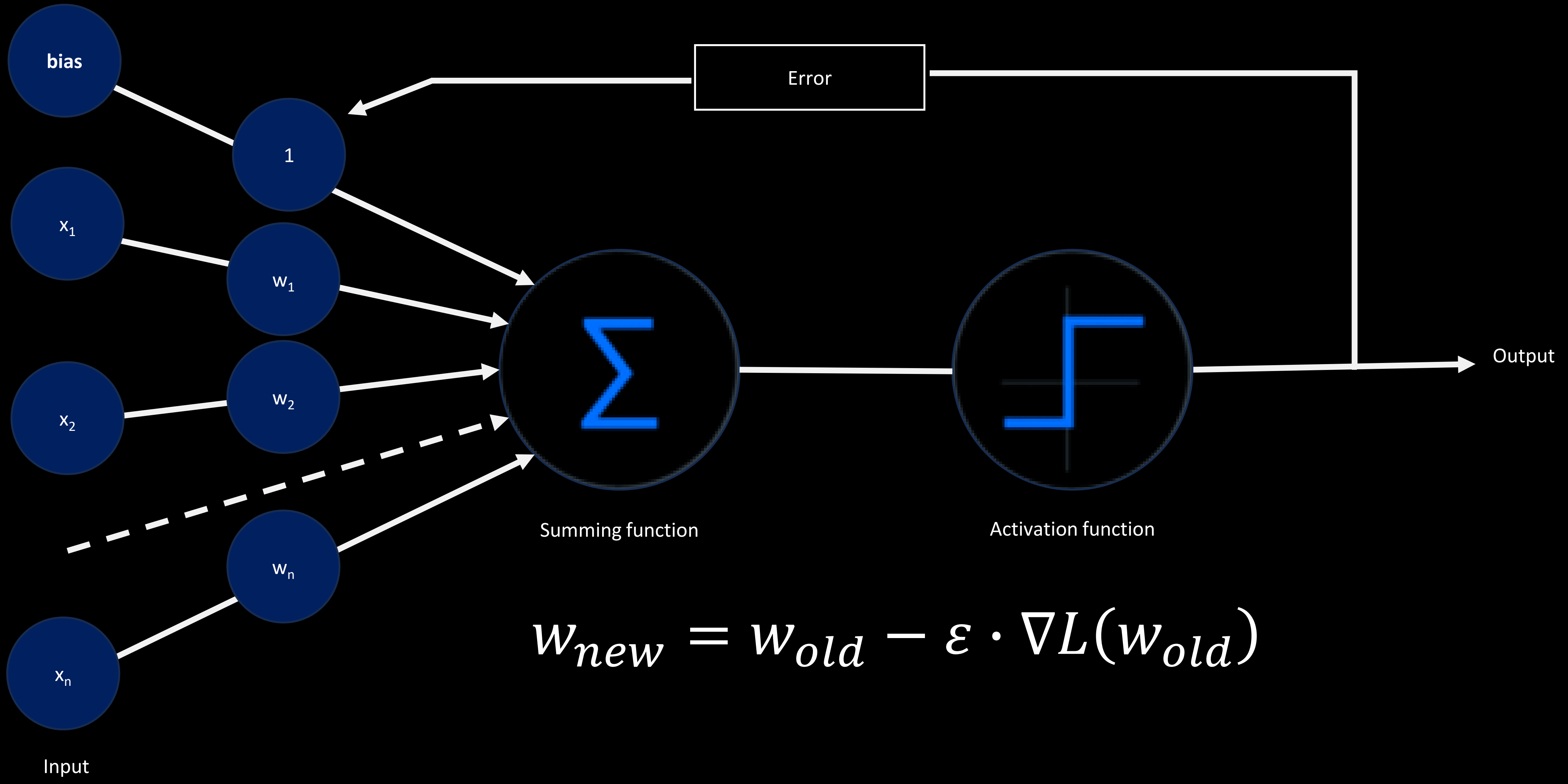


$$w_{new} = w_{old} + \varepsilon\,(y - \hat{y})x$$

Impact on Output with no Change in Data



The Perceptron



$$w_{new} = w_{old} - \varepsilon \cdot \nabla L(w_{old})$$

XOR Problem

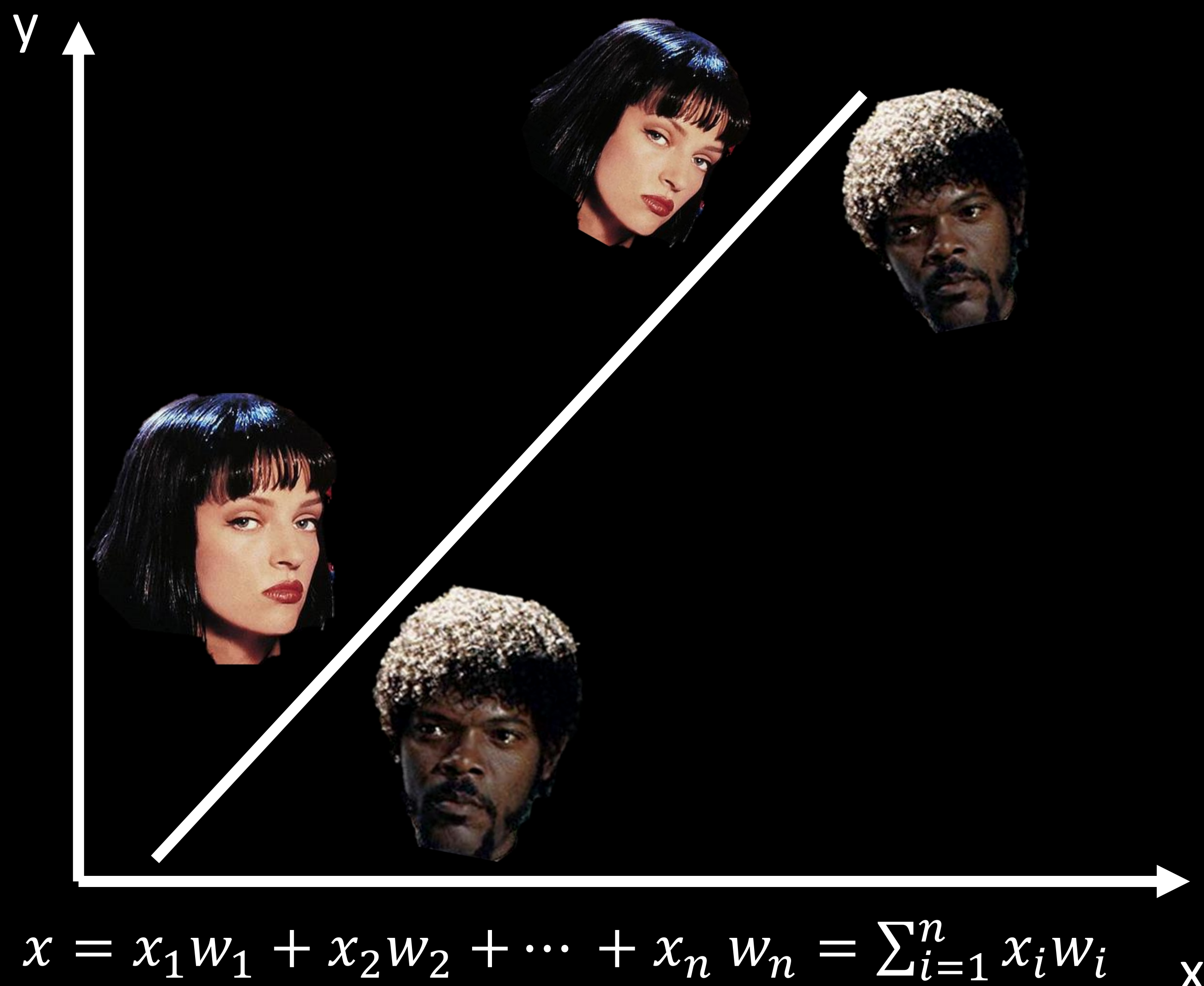
Marvin Minsky
(1927 – 2016)

Seymour Papert
(1928 – 2016)

A	B	A AND B	A OR B	A XOR B
0	0	1	0	0
1	0	0	1	1
0	1	0	1	1
1	1	1	1	0

Truth table for the logical functions AND, OR, and XOR.

Linearly Separable Classes



$$x = x_1 w_1 + x_2 w_2 + \cdots + x_n\, w_n = \sum_{i=1}^{n} x_i w_i$$

XOR Problem

Marvin Minsky
(1927 – 2016)

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Truth table for the logical functions AND, OR, and XOR.

Linearly Separable Classes

$$x = x_1 w_1 + x_2 w_2 + \cdots + x_n\, w_n = \sum_{i=1}^{n} x_i w_i$$

x

XOR Problem

Marvin Minsky
(1927 – 2016)

Seymour Papert
(1928 – 2016)

A	B	A AND B	A OR B	A XOR B
0	0	1	0	0
1	0	0	1	1
0	1	0	1	1
1	1	1	1	0

Truth table for the logical functions AND, OR, and XOR.

Linearly Separable Classes

$$x = x_1 w_1 + x_2 w_2 + \cdots + x_n\, w_n = \sum_{i=1}^{n} x_i w_i$$

XOR Problem

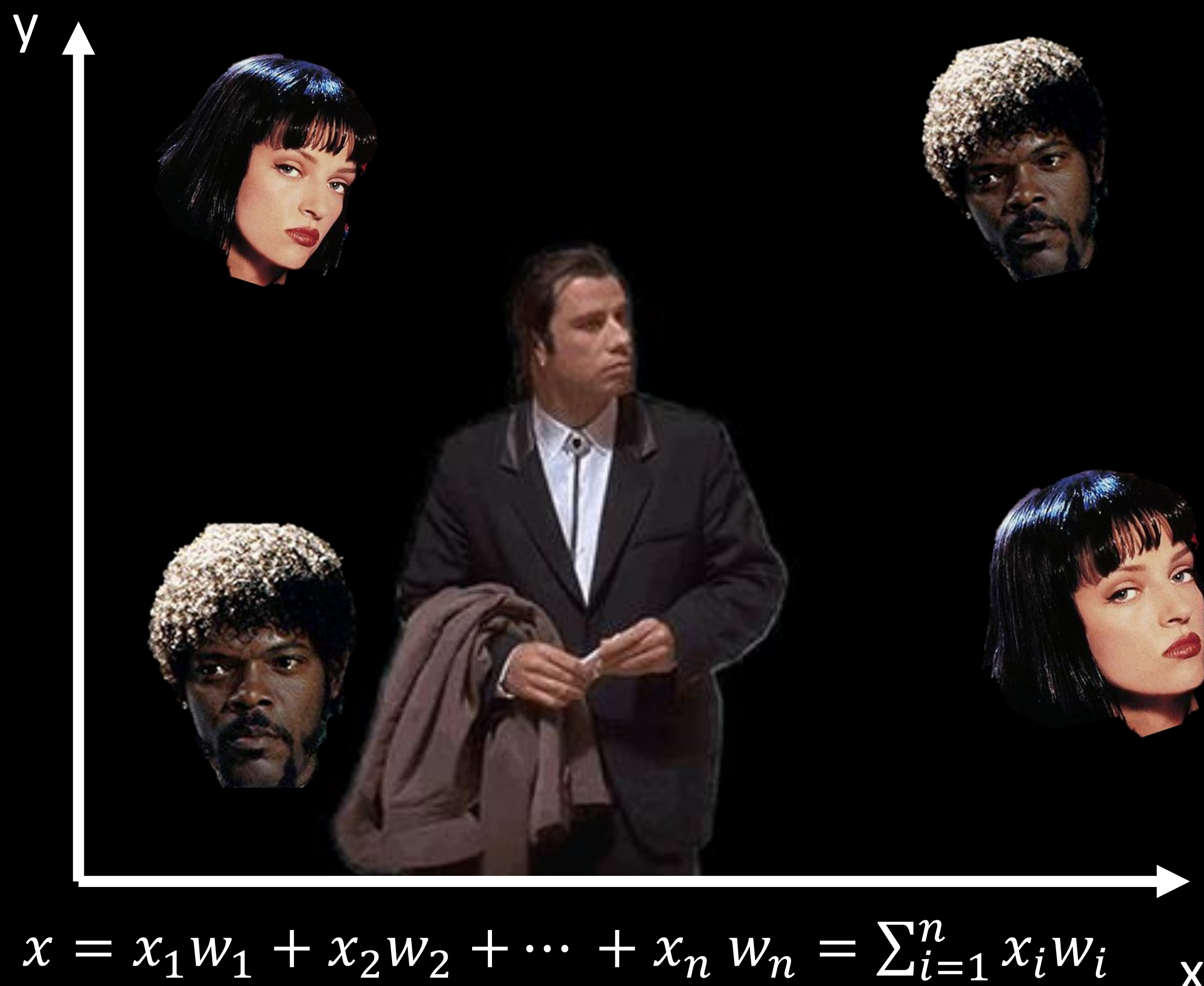
Marvin Minsky
(1927 – 2016)

Seymour Papert
(1928 – 2016)

A	B	A AND B	A OR B	A XOR B
0	0	1	0	0
1	0	0	1	1
0	1	0	1	1
1	1	1	1	0

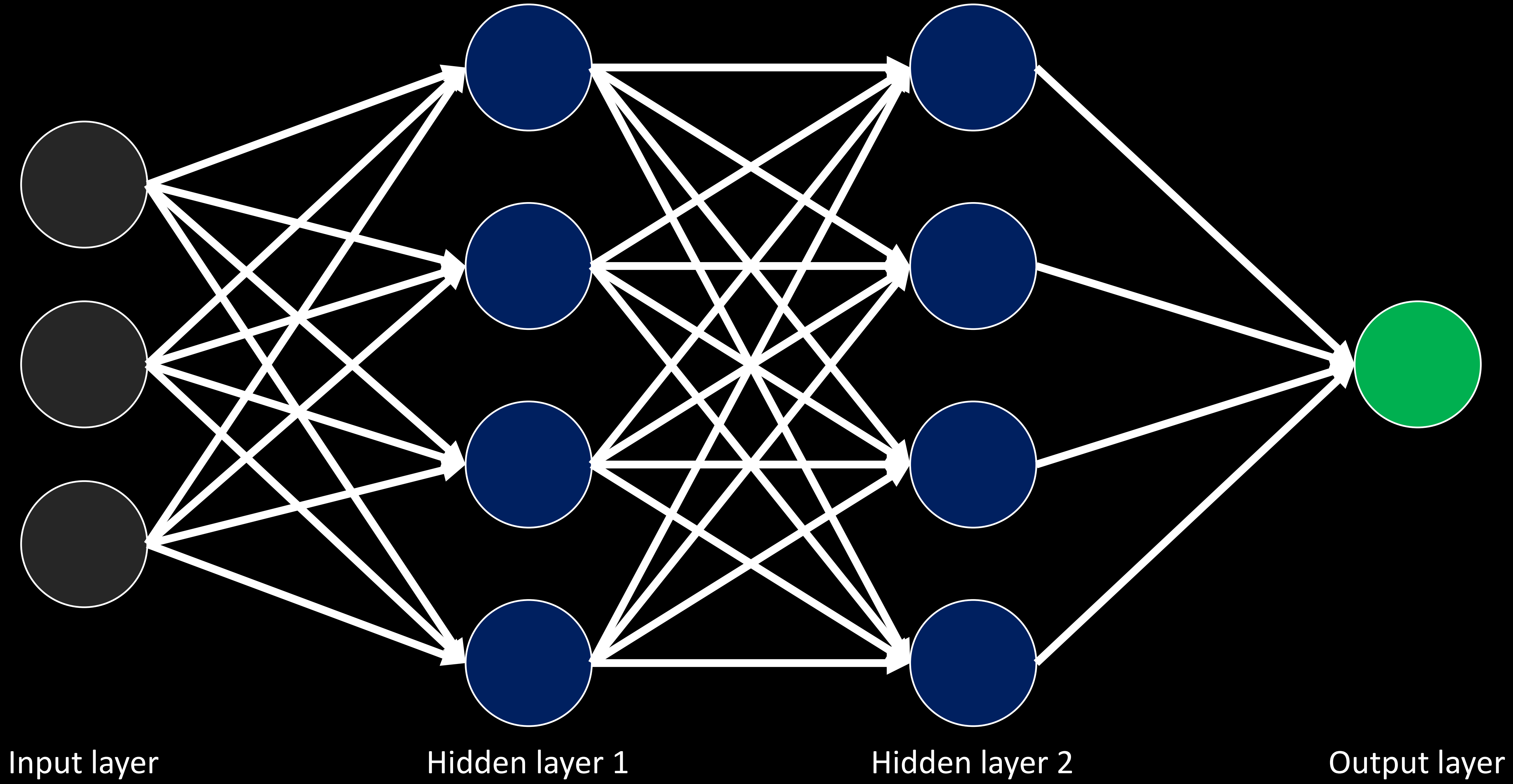
Truth table for the logical functions AND, OR, and XOR.

Linearly non-Separable Classes

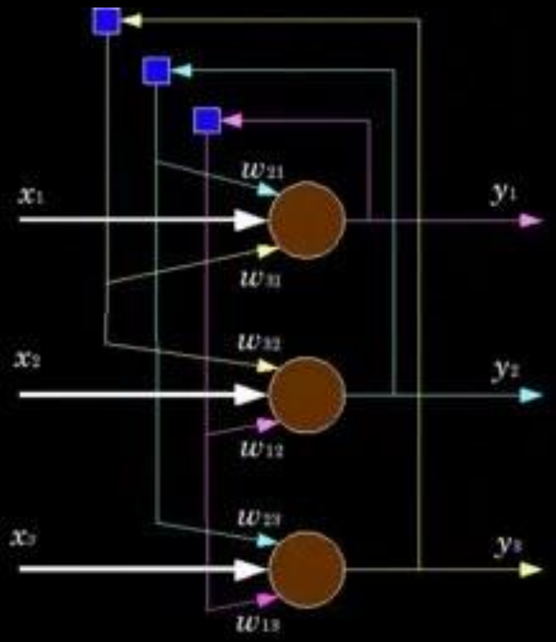


$$x = x_1 w_1 + x_2 w_2 + \cdots + x_n\, w_n = \sum_{i=1}^{n} x_i w_i$$

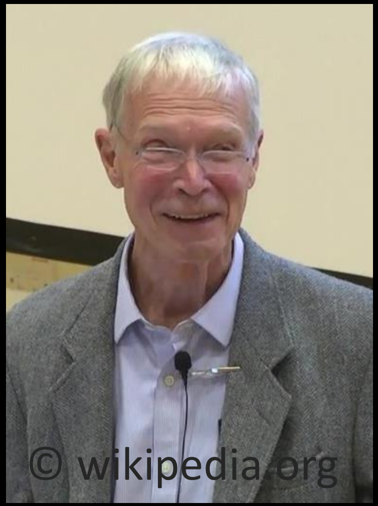
Hidden Layers and First AI Winter



Backpropagation and Novel Prize

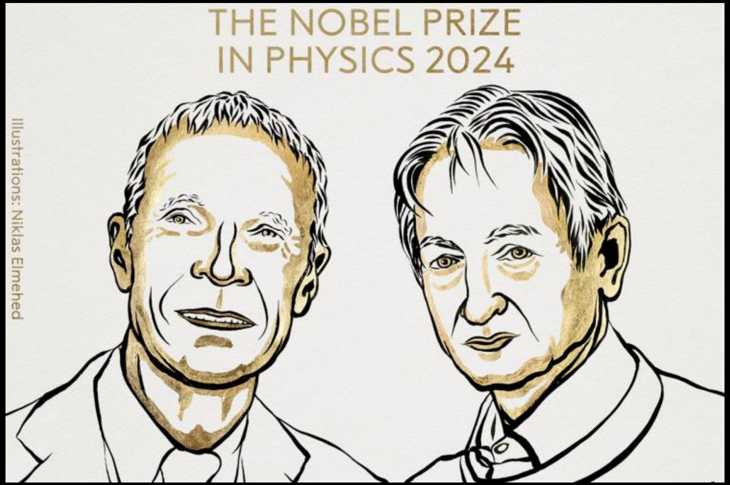


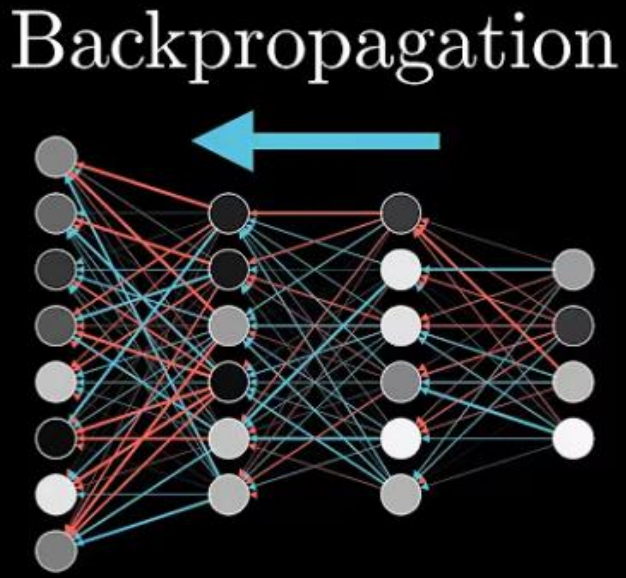
Hopfield Network Diagram with Three Neurons



John Hopfield
(1933 -)

Geoffrey Hinton
(1947 -)

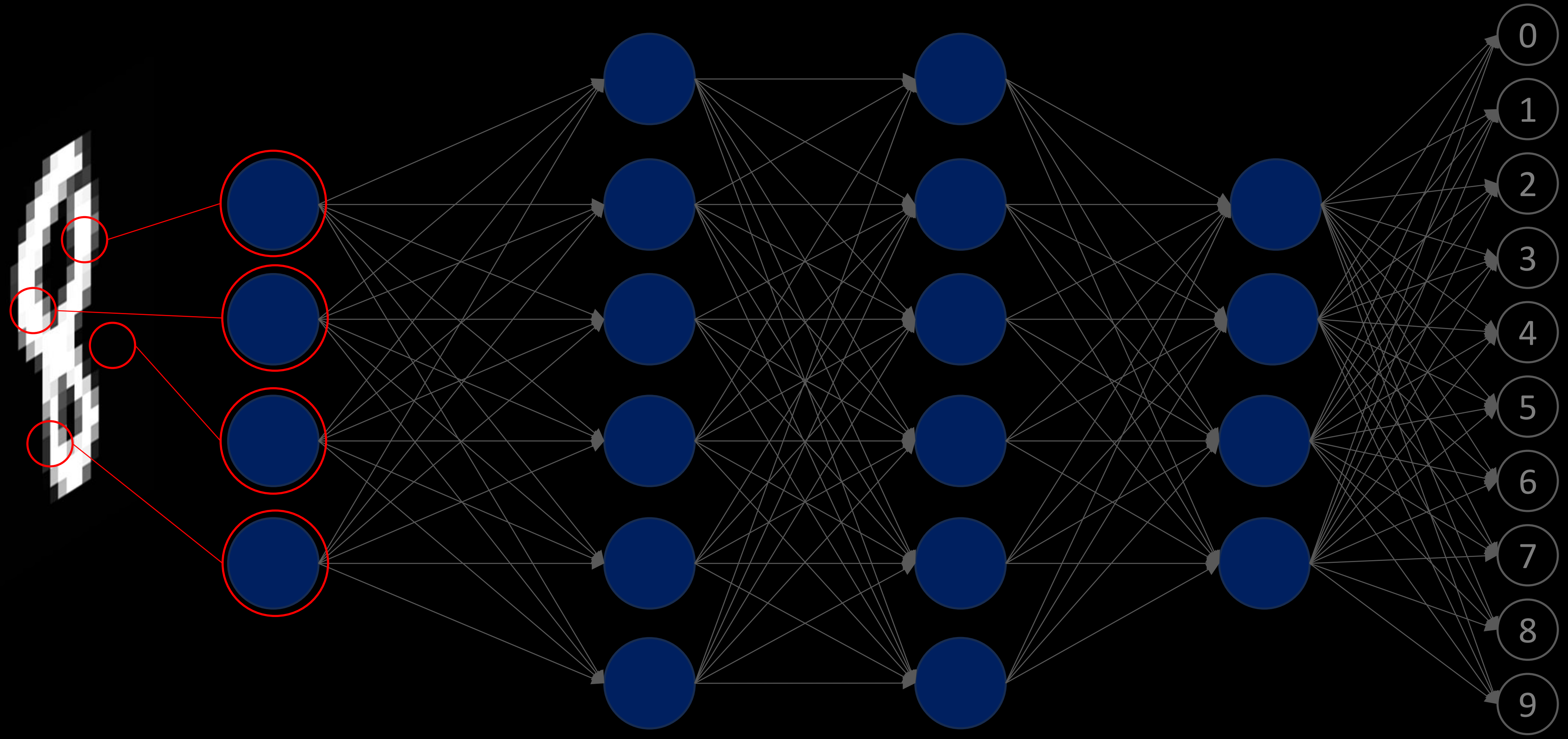




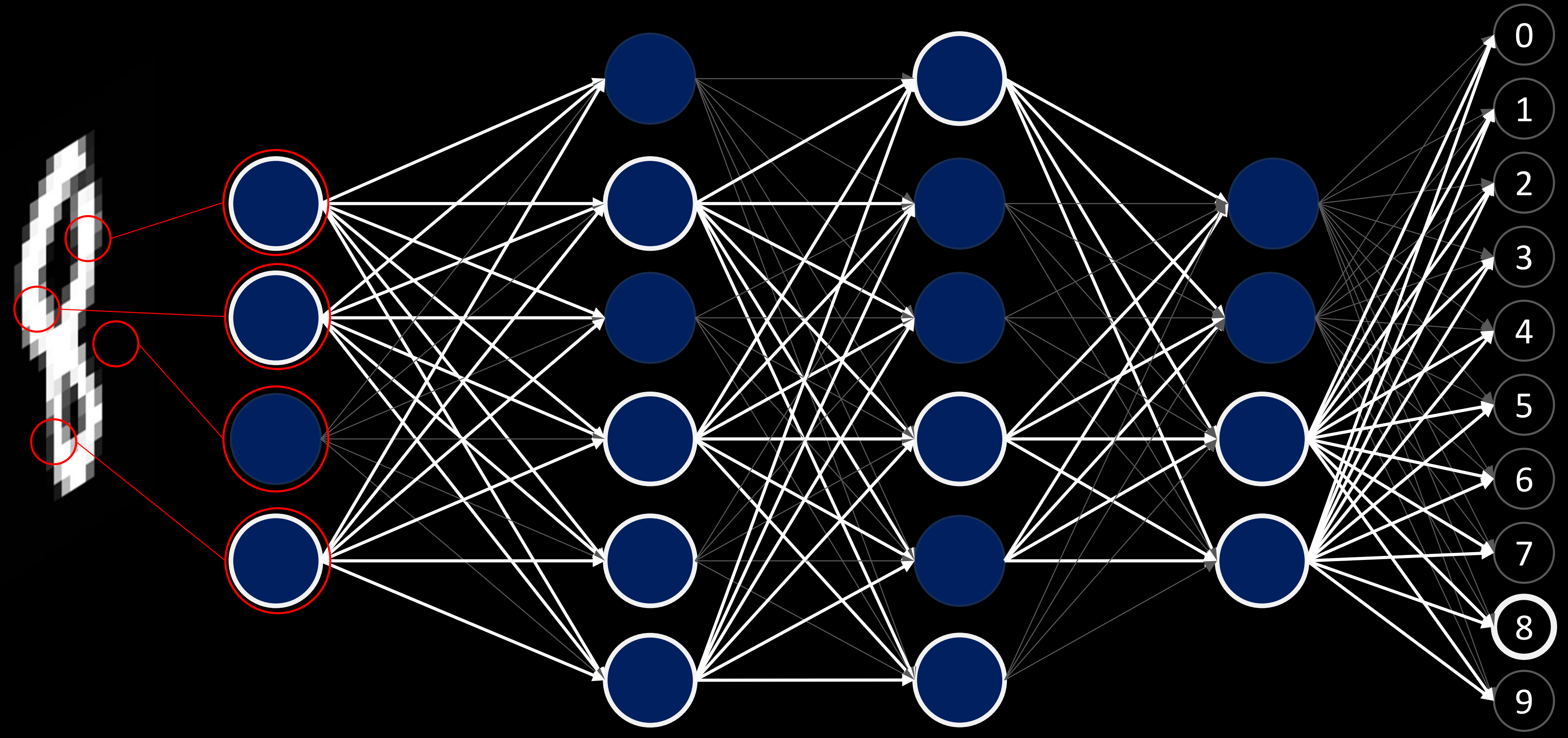
Backpropagation

@3blue1brown

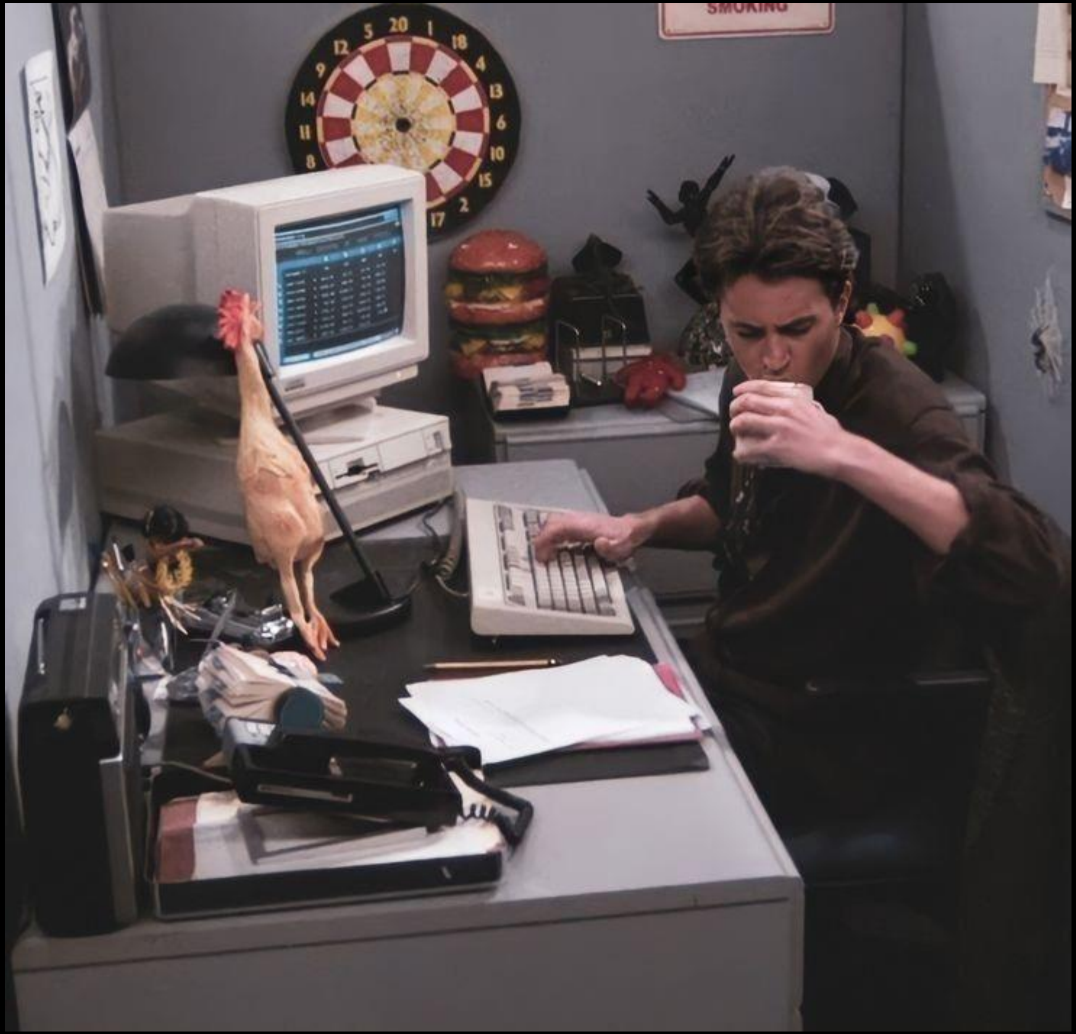
Artificial Neural Networks



Artificial Neural Networks



Second AI Winter



A frame from the TV series *Friends* (© Warner Bros. Television).

Astronomy, Astrophysics, AI

THE ASTRONOMICAL JOURNAL VOLUME 103, NUMBER 1 JANUARY 1992

AUTOMATED STAR/GALAXY DISCRIMINATION WITH NEURAL NETWORKS

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Department of Astronomy, University of Minnesota, Minneapolis, Minnesota 55455
Received 12 June 1991; revised 29 August 1991

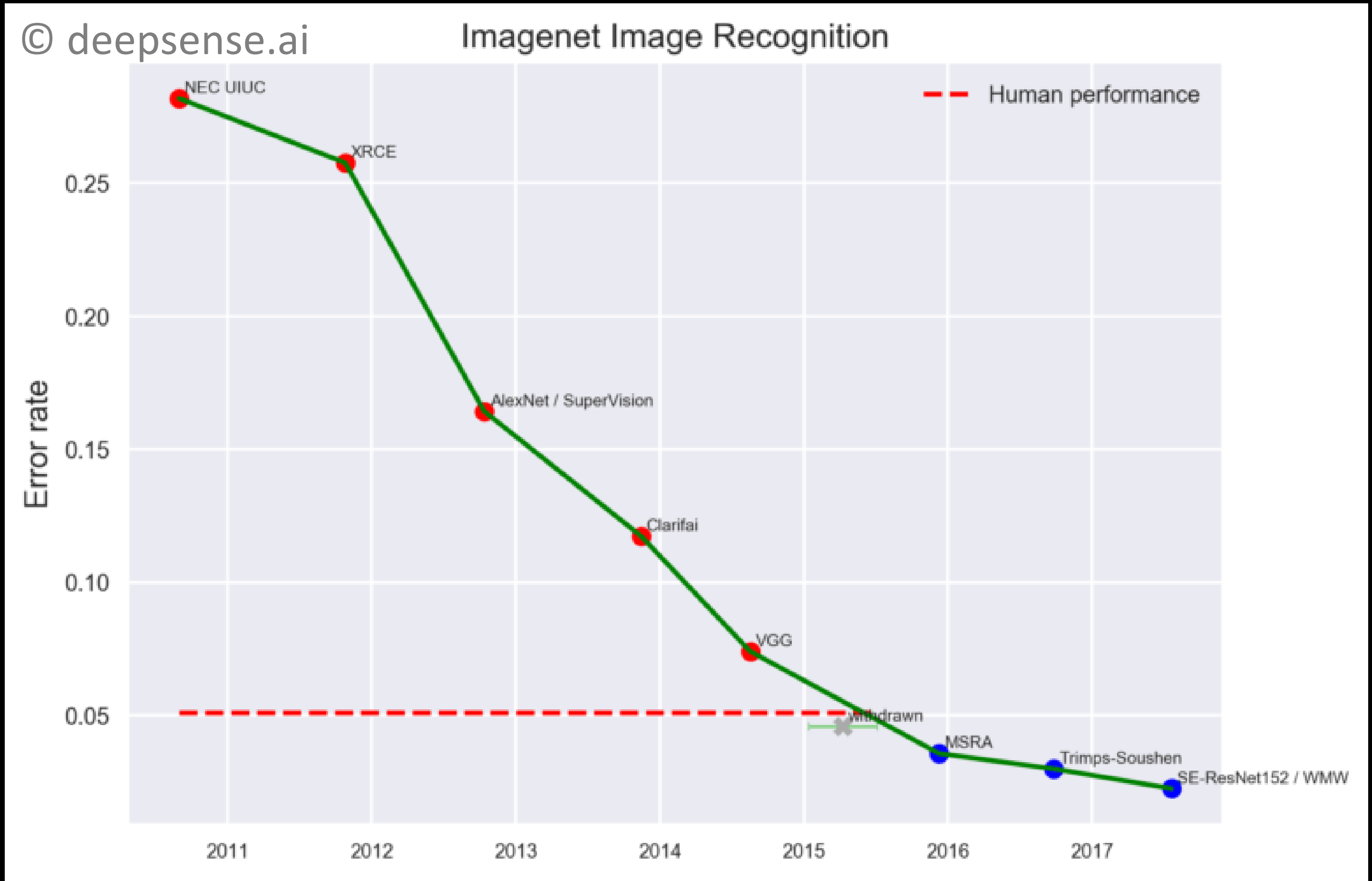
ABSTRACT

We discuss progress in the development of automatic star/galaxy discriminators for processing images generated by the University of Minnesota Automated Plate Scanner (APS) for cataloging the first epoch Palomar Sky Survey. Classifications are based on 14 image parameters computed for each object detected by the APS operating in a threshold densitometry mode. It is shown that a number of parameter spaces formed with these vector elements are effective in separating a sample into the two basic populations of stellar and nonstellar objects. An artificial intelligence technique known as a neural network is employed to perform the image classification. We have experimented with a simple linear classifier known as a perceptron, as well as with a more sophisticated backpropagation neural network with the result that we are able to attain classification success rates of 99% for galaxy images with $B \leqslant 18.5$ and above 95% for the magnitude range $18.5 \leqslant B \leqslant 19.5$. The analysis presented here uses a training dataset consisting of 2665 galaxies and 2082 stars, along with a test sample of 936 galaxies and 2378 stars. We have determined the success rate of these classifiers as a function of image diameter and

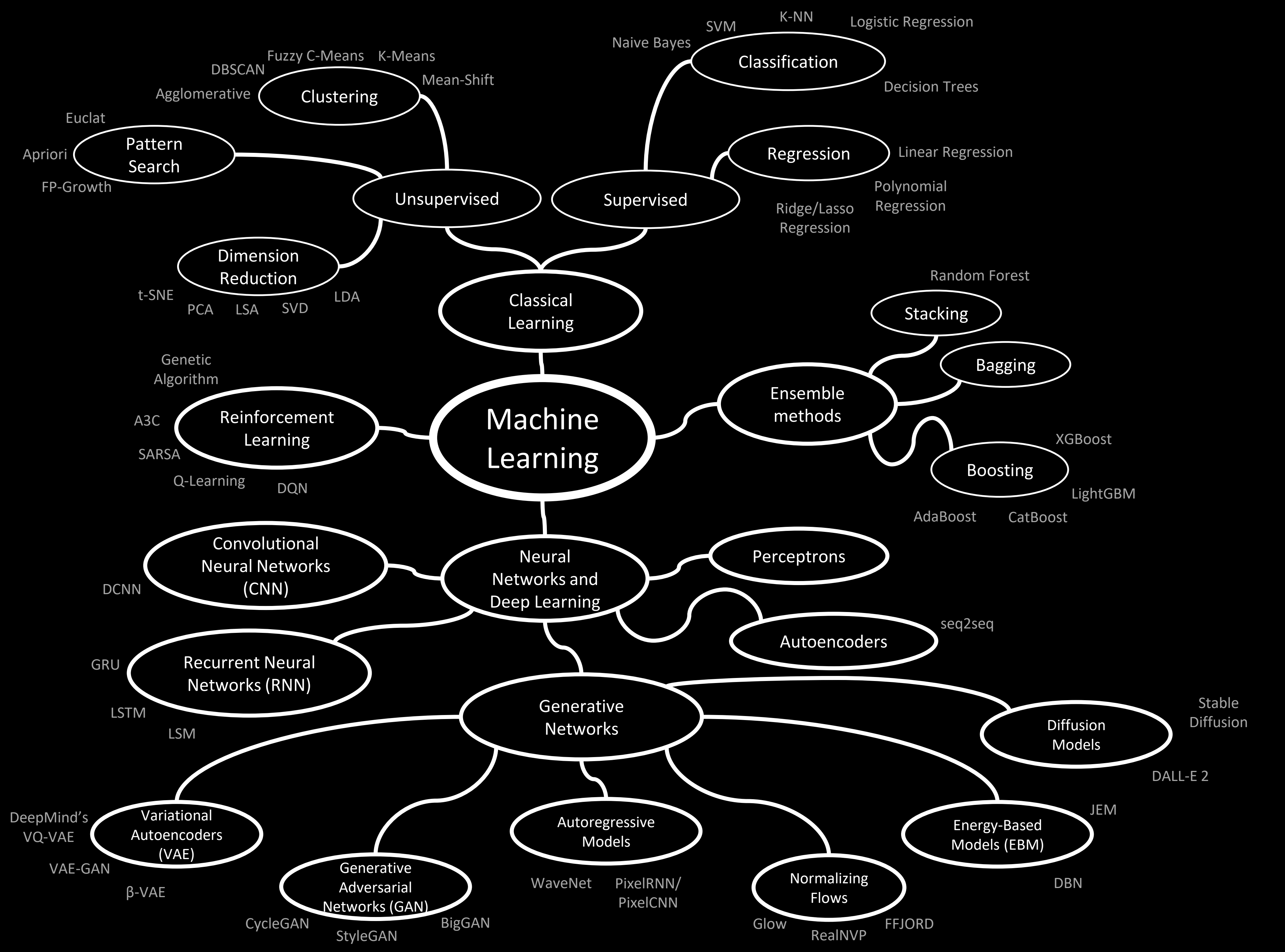
Odewahn, S.C., et al. (1992). Automated Star/Galaxy Discrimination with Neural Networks. In: MacGillivray, H.T., Thomson, E.B. (eds) *Digitised Optical Sky Surveys*. *Astrophysics and Space Science Library*, vol 174. Springer, Dordrecht. https://doi.org/10.1007/978-94-011-2472-0_28

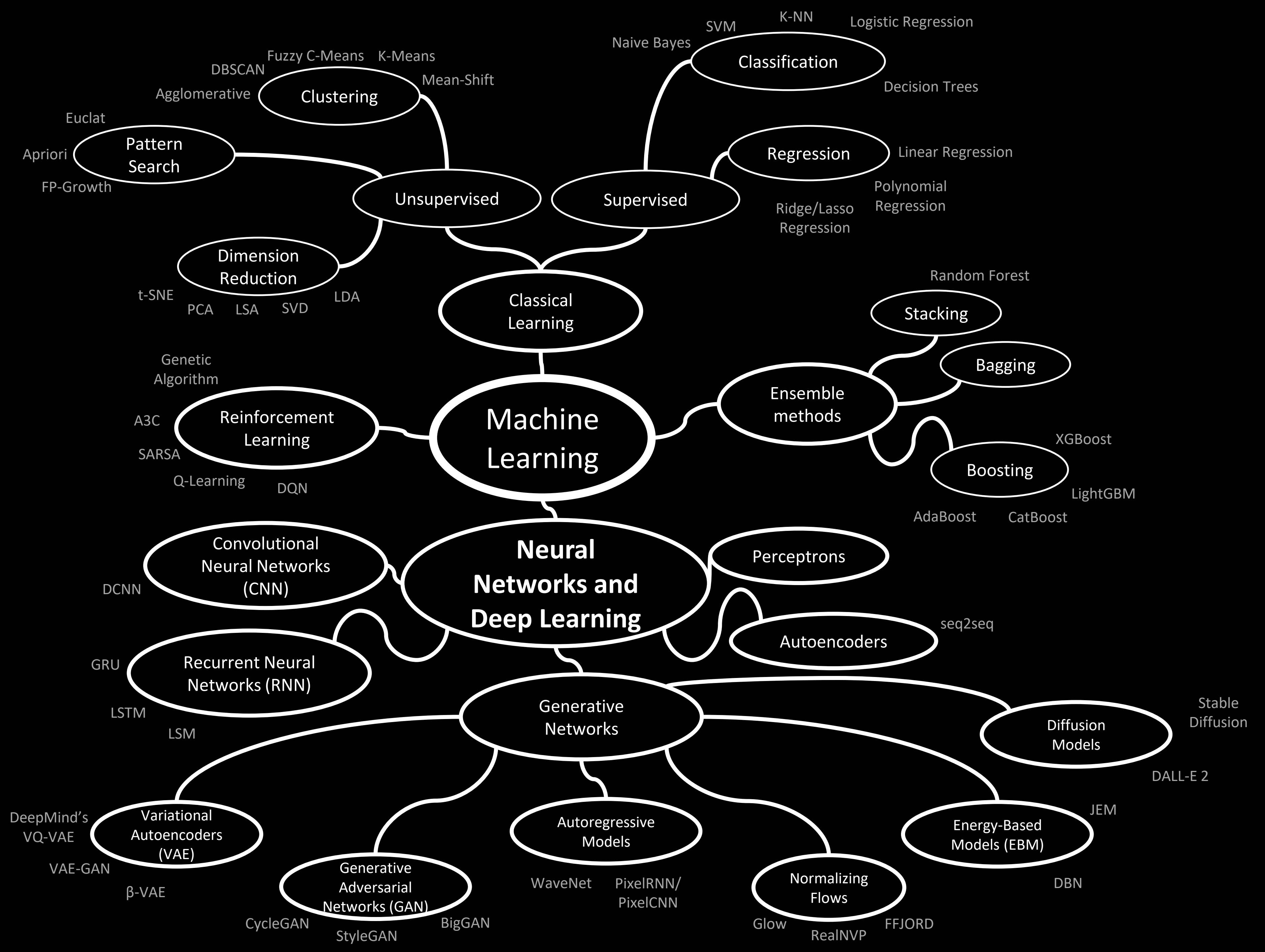
ImageNet Large Scale Visual Recognition Challenge (ILSVRC)

ImageNet Image Catalog
(14,000,000 images, 20,000 classes)



Error Rate Curve of Classifiers
(---- average error rate for humans)

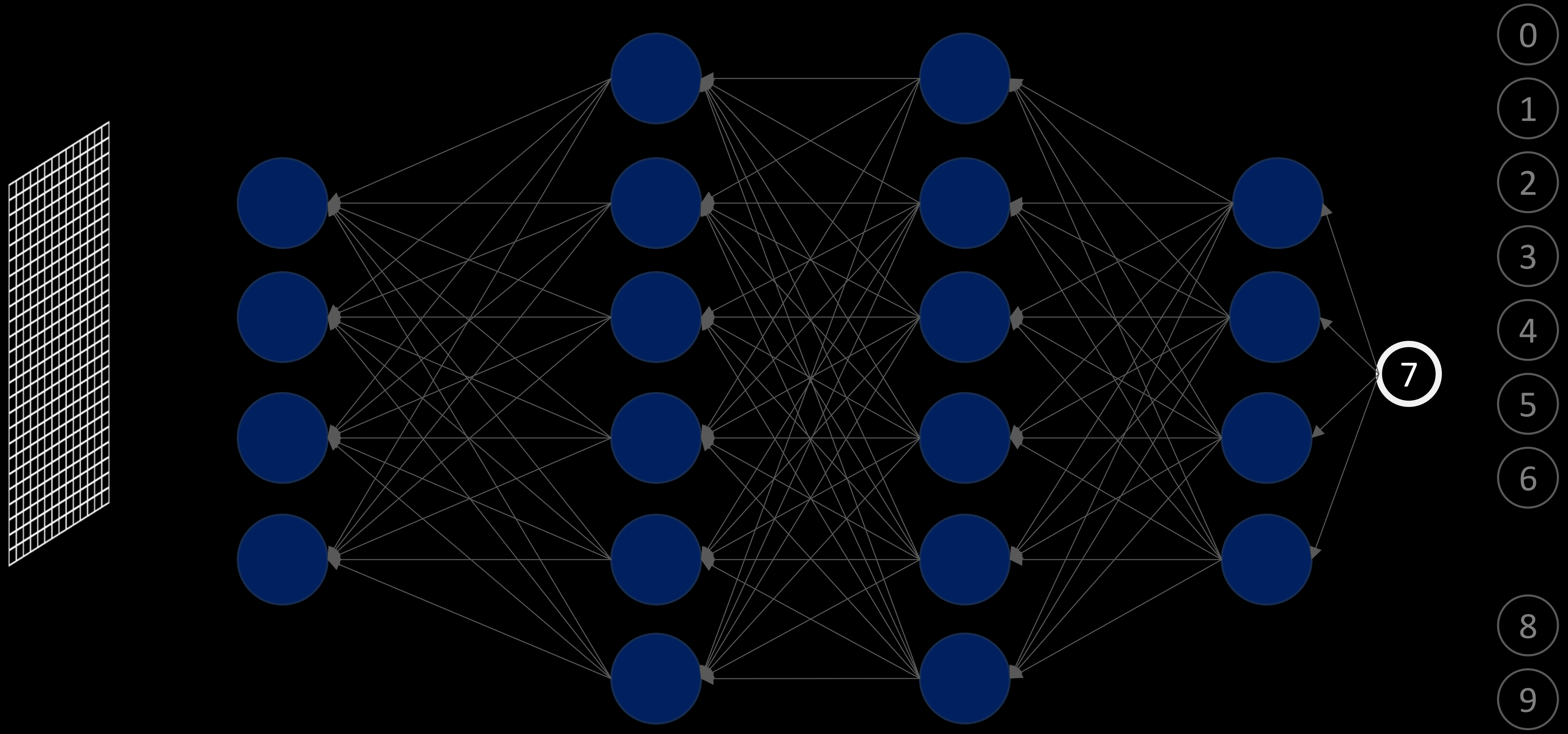

Machine Learning
Classical Learning
Unsupervised
Supervised
Clustering
Fuzzy C-Means
K-Means
DBSCAN
Mean-Shift
Agglomerative
Pattern Search
Euclat
Apriori
FP-Growth
Dimension Reduction
t-SNE
PCA
LSA
SVD
LDA
Classification
Naive Bayes
SVM
K-NN
Logistic Regression
Decision Trees
Regression
Linear Regression
Polynomial Regression
Ridge/Lasso Regression
Reinforcement Learning
Genetic Algorithm
A3C
SARSA
Q-Learning
DQN
Ensemble methods
Stacking
Random Forest
Bagging
Boosting
XGBoost
LightGBM
AdaBoost
CatBoost
Neural Networks and Deep Learning
Convolutional Neural Networks (CNN)
DCNN
Recurrent Neural Networks (RNN)
GRU
LSTM
LSM
Perceptrons
Autoencoders
seq2seq
Generative Networks
Diffusion Models
Stable Diffusion
DALL-E 2
Variational Autoencoders (VAE)
DeepMind's VQ-VAE
VAE-GAN
β-VAE
Generative Adversarial Networks (GAN)
CycleGAN
StyleGAN
BigGAN
Autoregressive Models
WaveNet
PixelRNN/ PixelCNN
Normalizing Flows
Glow
RealNVP
FFJORD
Energy-Based Models (EBM)
JEM
DBN


Machine Learning
Classical Learning
Unsupervised
Supervised
Clustering
DBSCAN
Fuzzy C-Means
K-Means
Mean-Shift
Agglomerative
Pattern Search
Euclat
Apriori
FP-Growth
Dimension Reduction
t-SNE
PCA
LSA
SVD
LDA
Classification
Naive Bayes
SVM
K-NN
Logistic Regression
Decision Trees
Regression
Linear Regression
Polynomial Regression
Ridge/Lasso Regression
Ensemble methods
Stacking
Random Forest
Bagging
Boosting
XGBoost
LightGBM
AdaBoost
CatBoost
Reinforcement Learning
Genetic Algorithm
A3C
SARSA
Q-Learning
DQN
Neural Networks and Deep Learning
Convolutional Neural Networks (CNN)
DCNN
Recurrent Neural Networks (RNN)
GRU
LSTM
LSM
Perceptrons
Autoencoders
seq2seq
Generative Networks
Diffusion Models
Stable Diffusion
DALL-E 2
Variational Autoencoders (VAE)
DeepMind's VQ-VAE
VAE-GAN
β-VAE
Generative Adversarial Networks (GAN)
CycleGAN
StyleGAN
BigGAN
Autoregressive Models
WaveNet
PixelRNN/ PixelCNN
Normalizing Flows
Glow
RealNVP
FFJORD
Energy-Based Models (EBM)
JEM
DBN

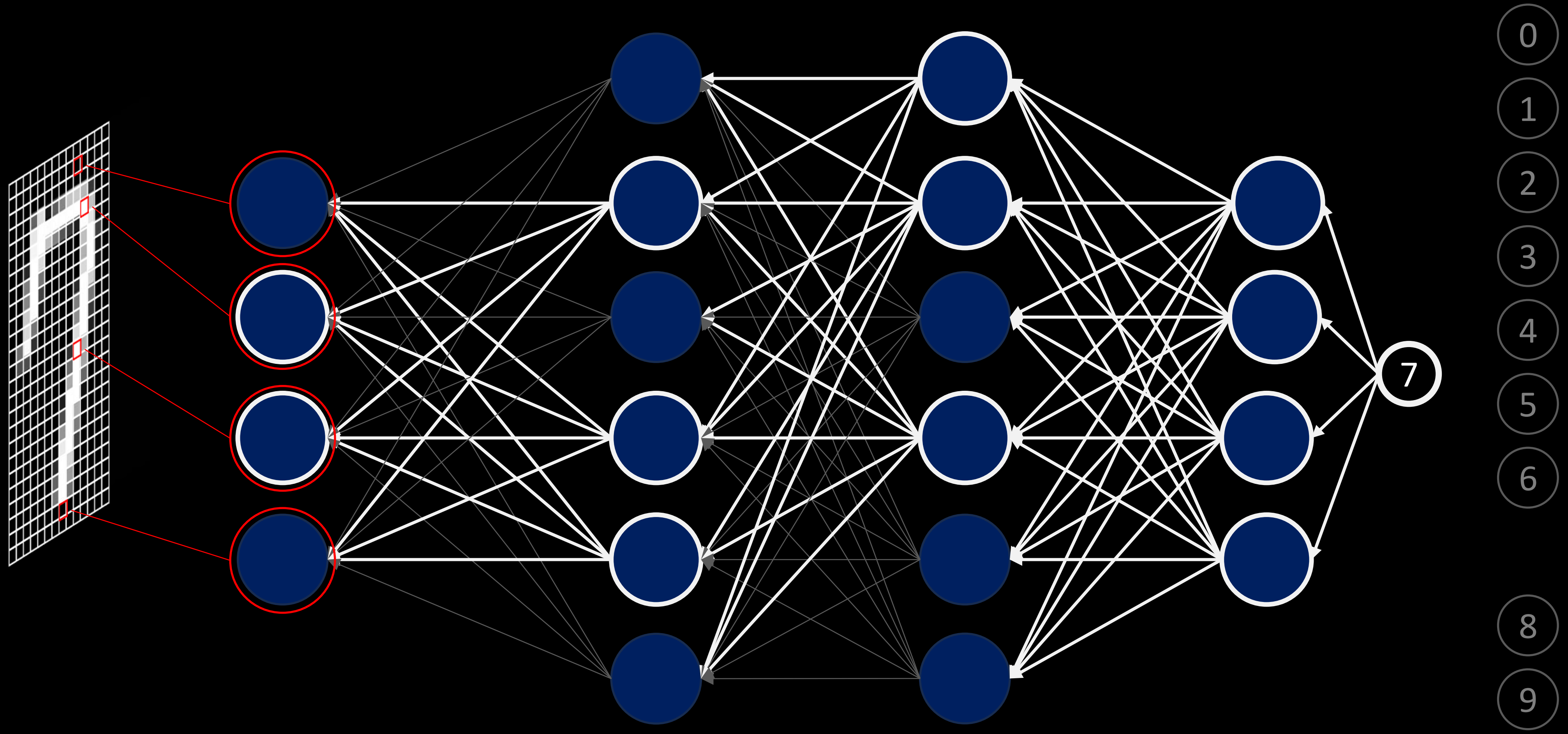
Generative Networks

	Variational Autoencoders (VAE)	Generative Adversarial Networks (GAN)	Autoregressive Models	Normalizing Flows	Energy-Based Models (EBM)	Diffusion Models
	β-VAE	CycleGAN	WaveNet	Glow	JEM	DALL-E 2
	VAE-GAN	StyleGAN	PixelRNN/ PixelCNN	RealNVP	DBN	Stable Diffusion
	DeepMind's VQ-VAE	BigGAN		FFJORD		

What is a Generative Model?

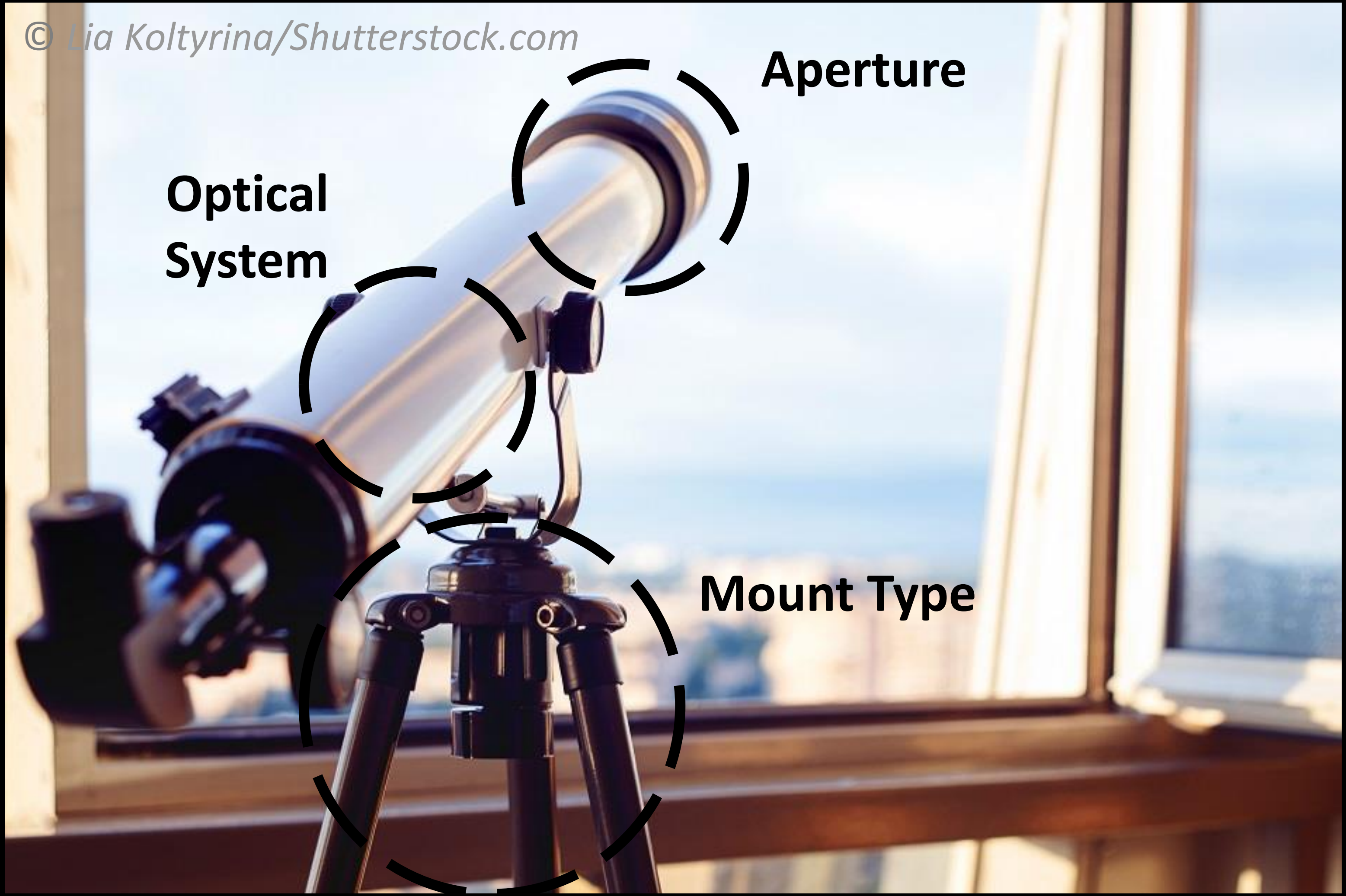


What is a Generative Model?



How Can We Describe a Telescope?

How Can We Describe a Telescope?



How Can We Describe a Telescope?

{

Aperture

Optical System

Mount Type

}

How Can We Describe a Telescope?

{

Aperture
Optical System
Mount Type

…

…

…

}

How Can We Describe Everything?

{

Parameter 1
Parameter 2
Parameter 3

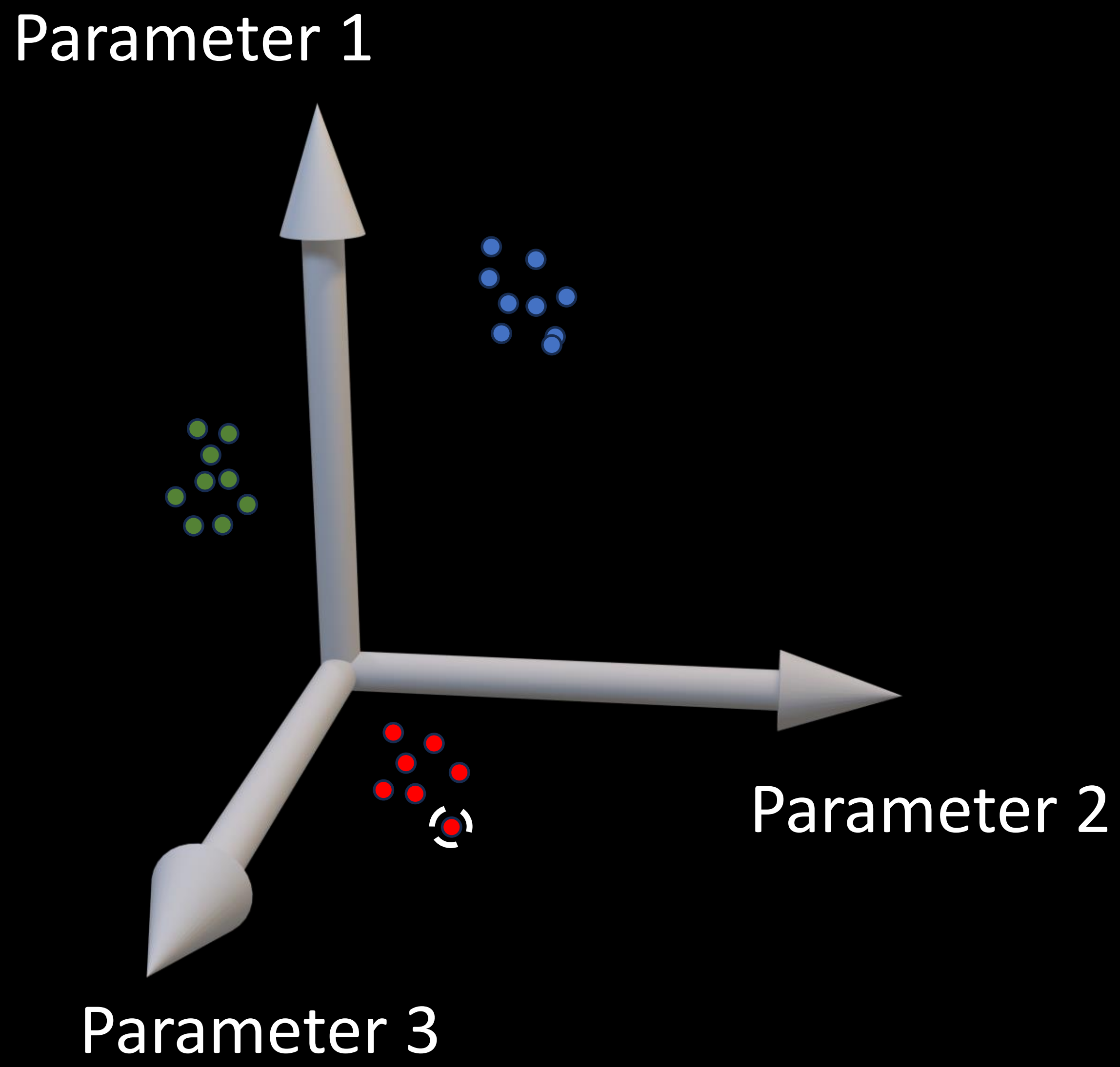
...

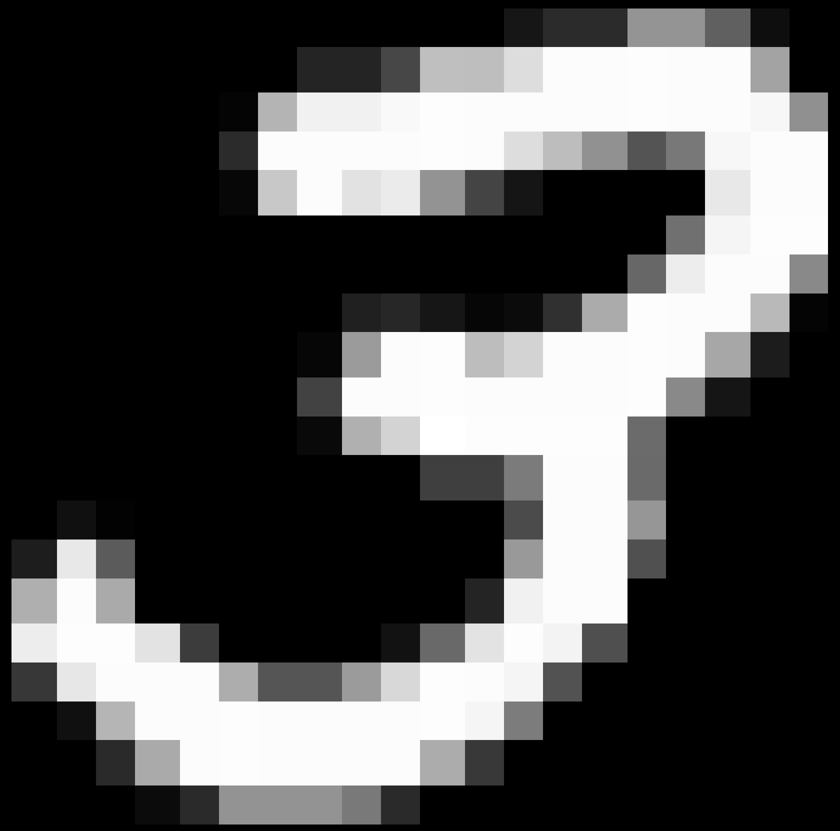
...

...

}

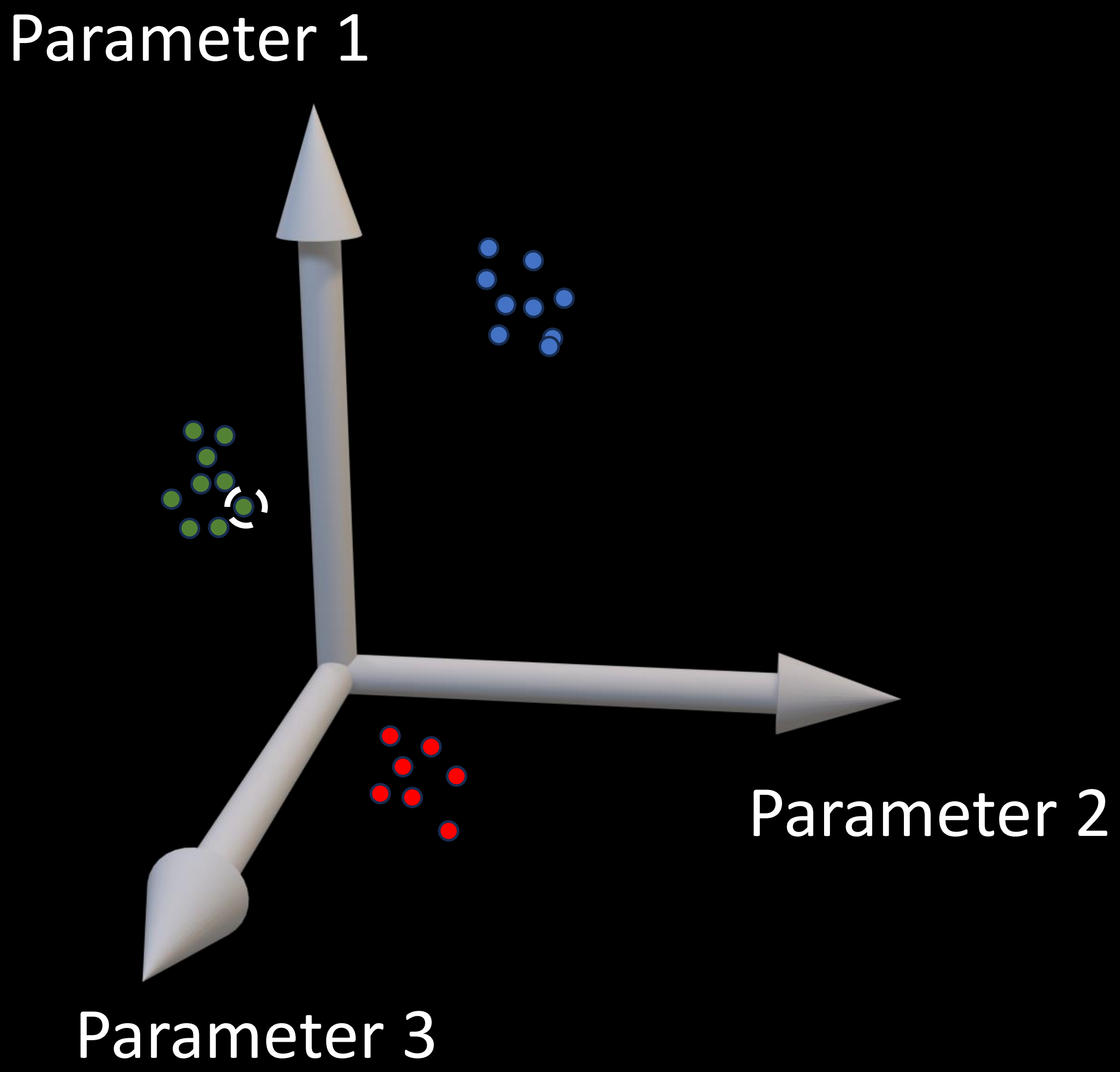
Latent Space

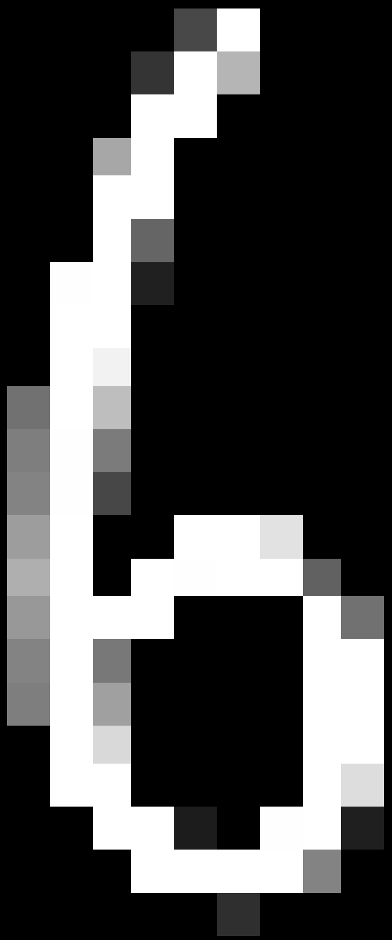




a lower-dimensional space that captures the essential features of the data

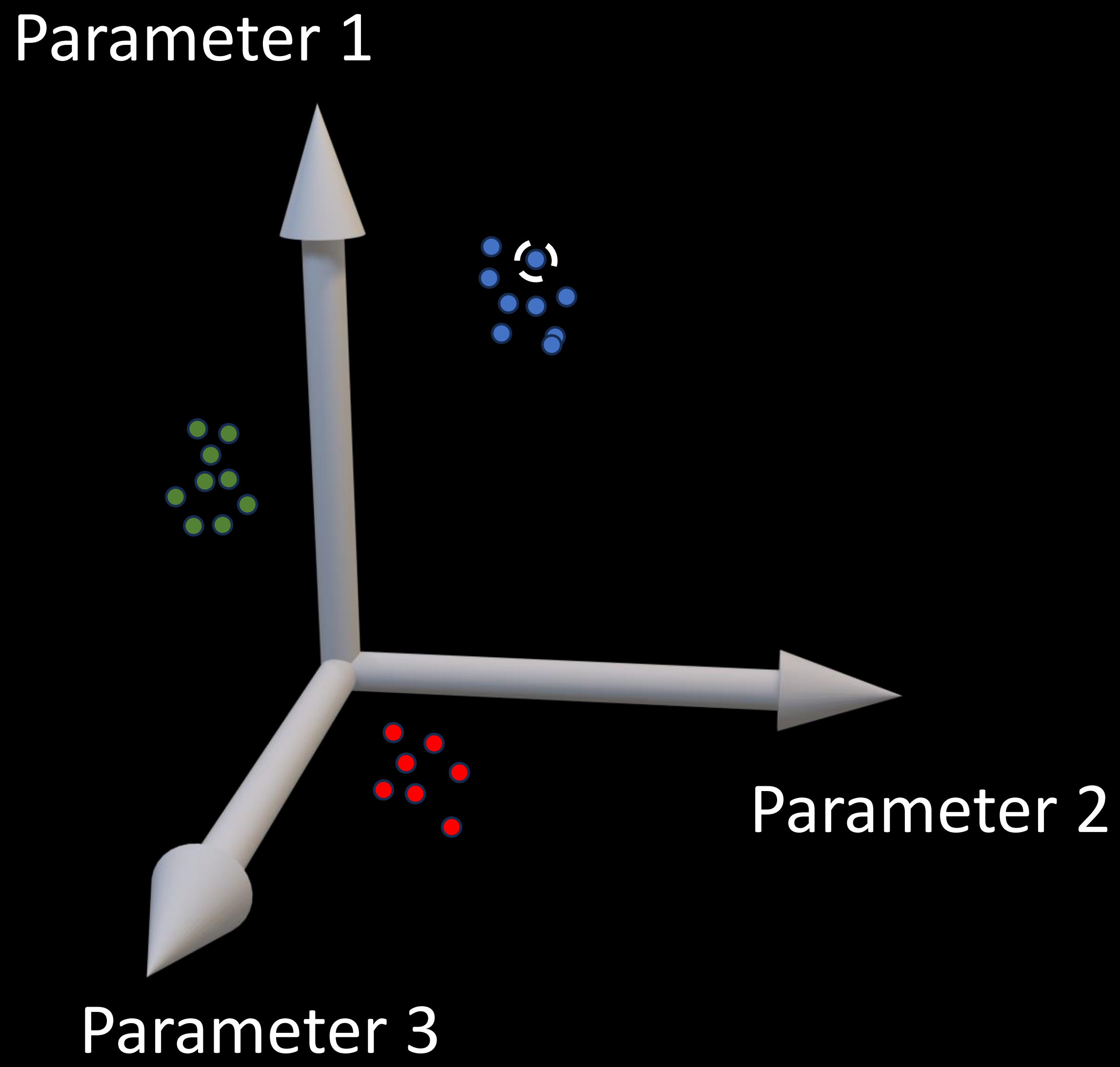
Latent Space

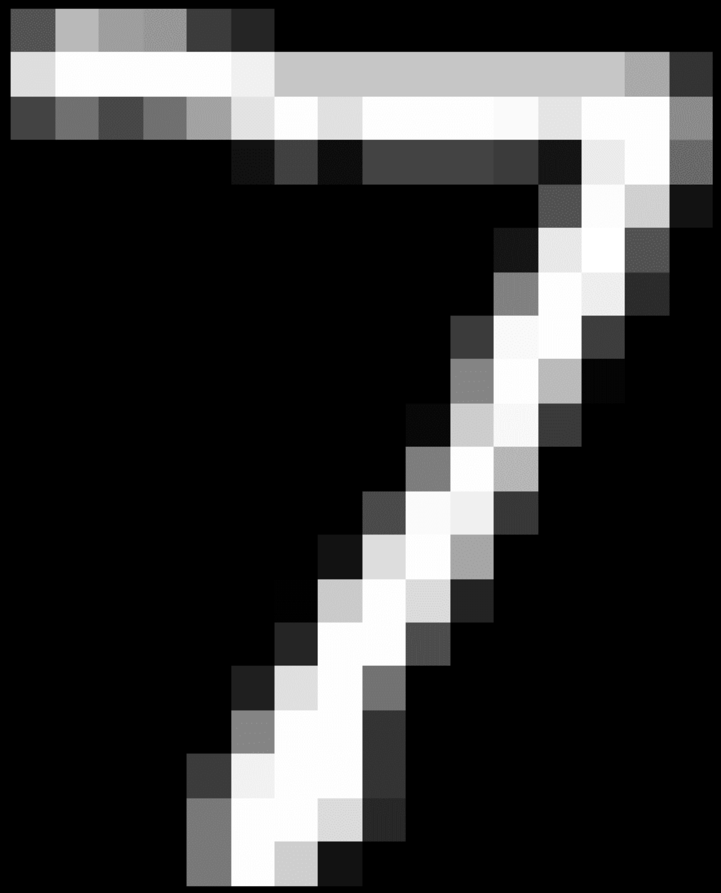




a lower-dimensional space that captures the essential features of the data

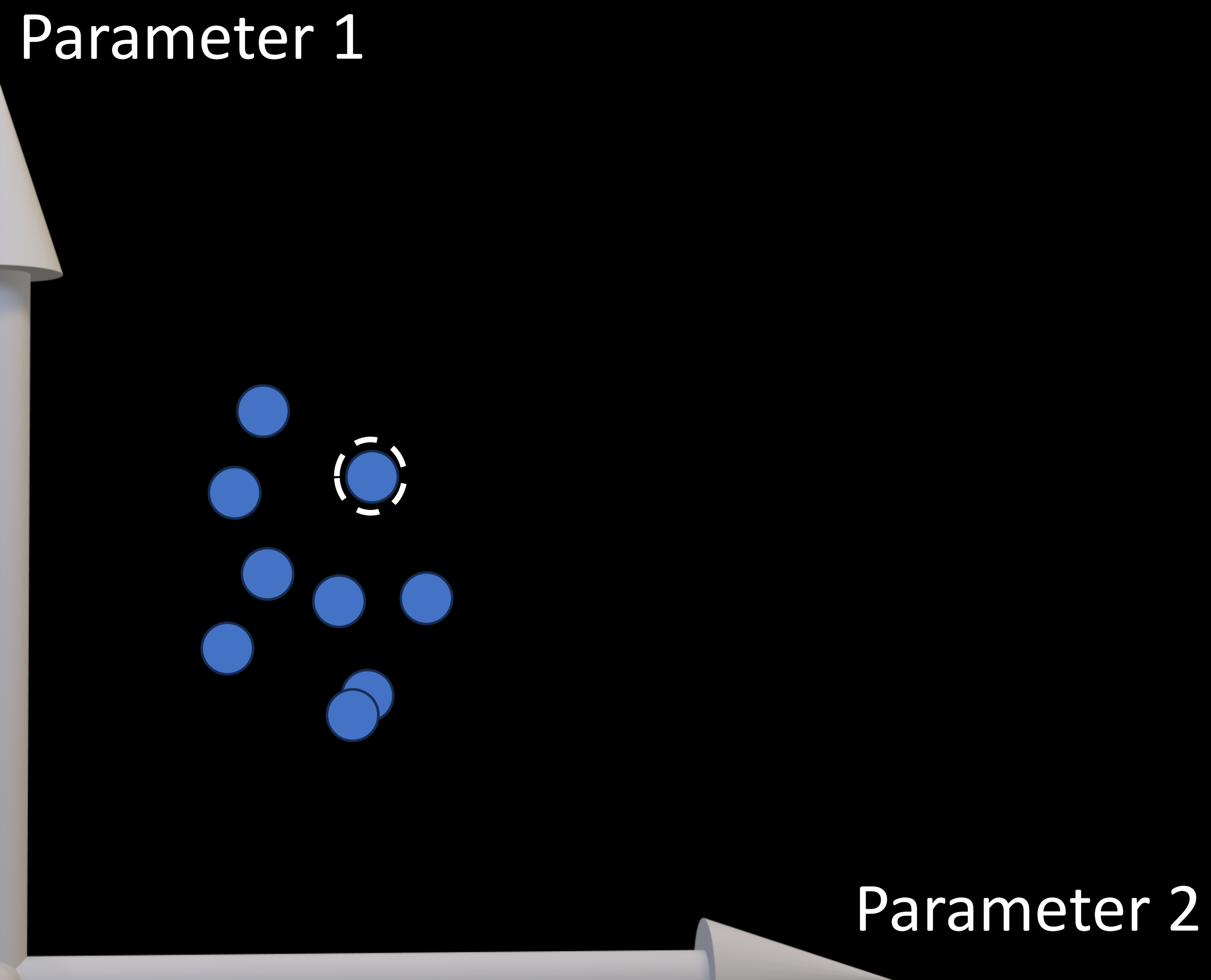
Latent Space

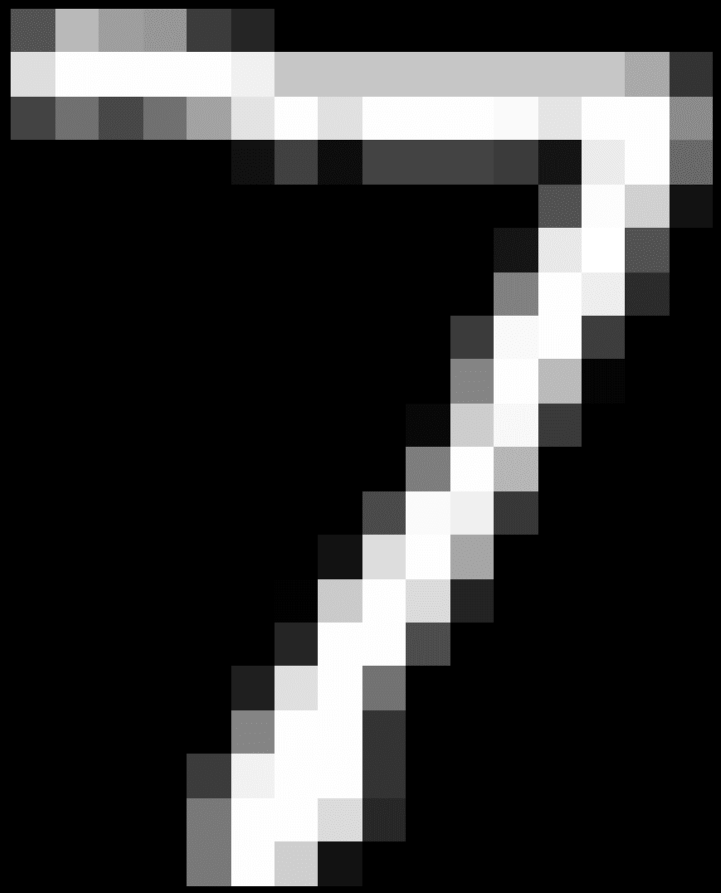




a lower-dimensional space that captures the essential features of the data

Generation from the Latent Space





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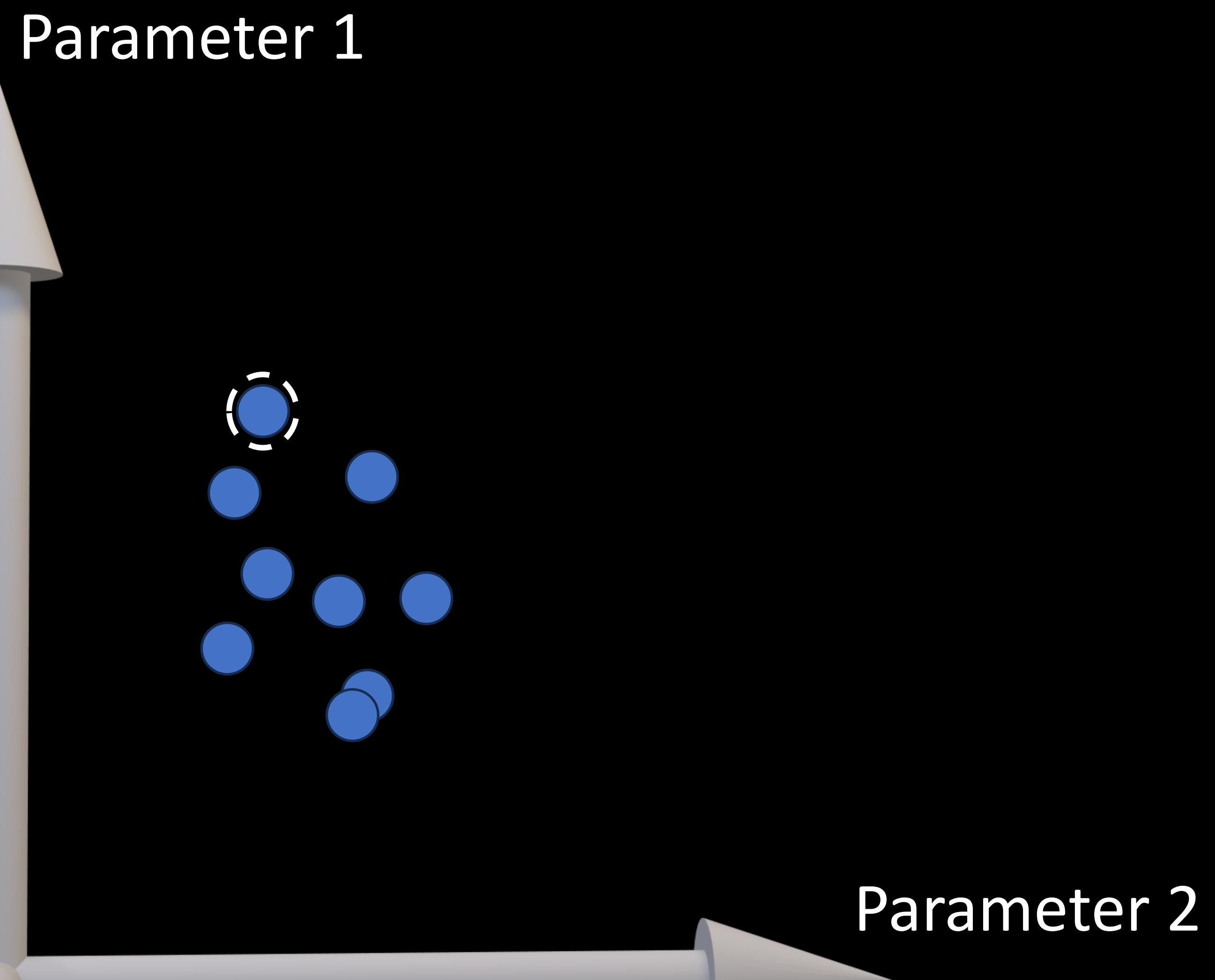

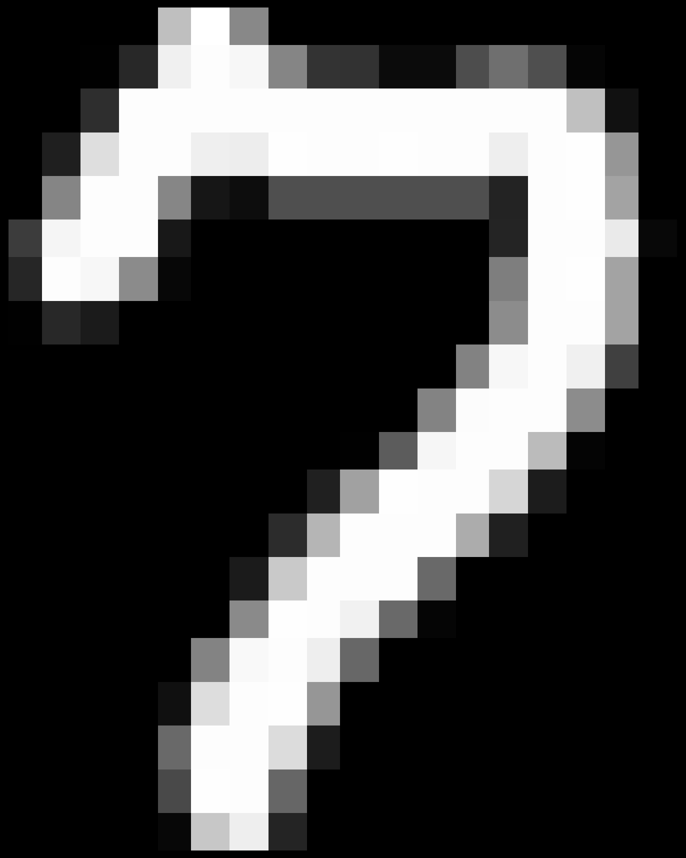

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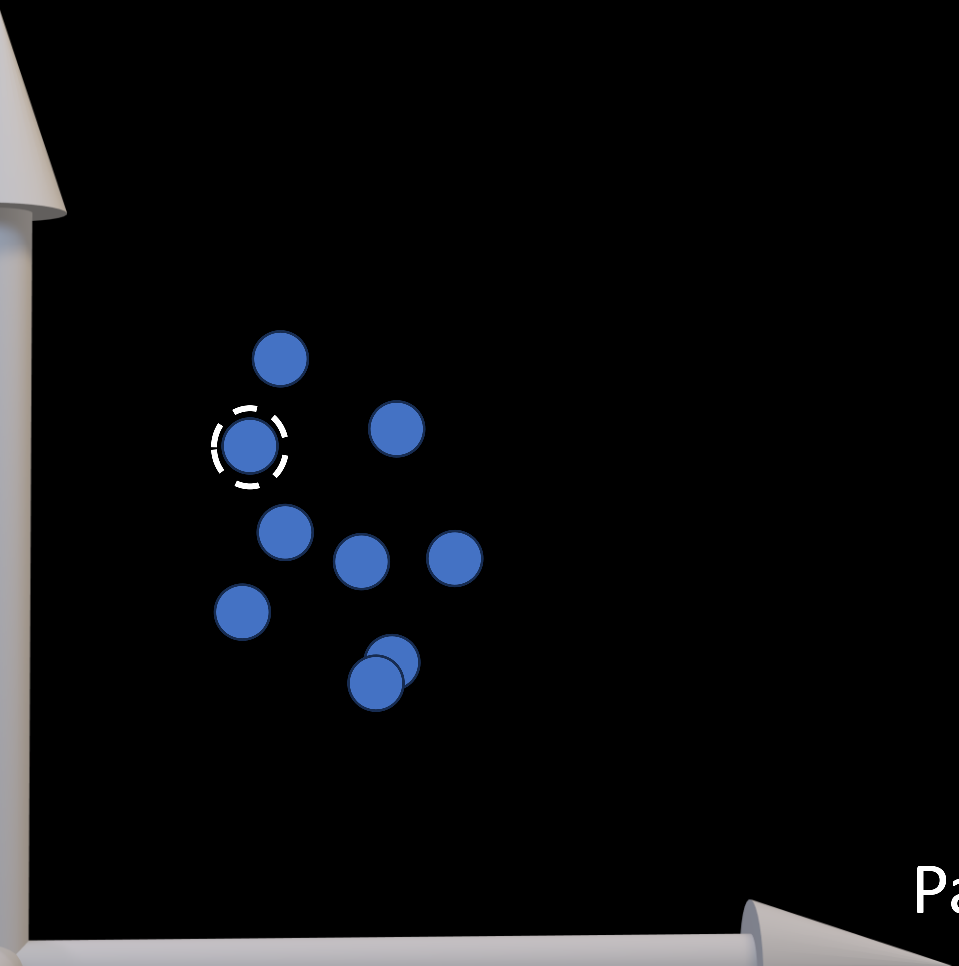

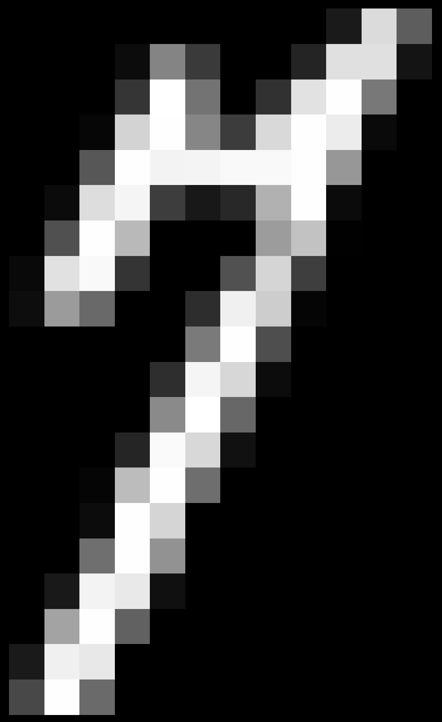

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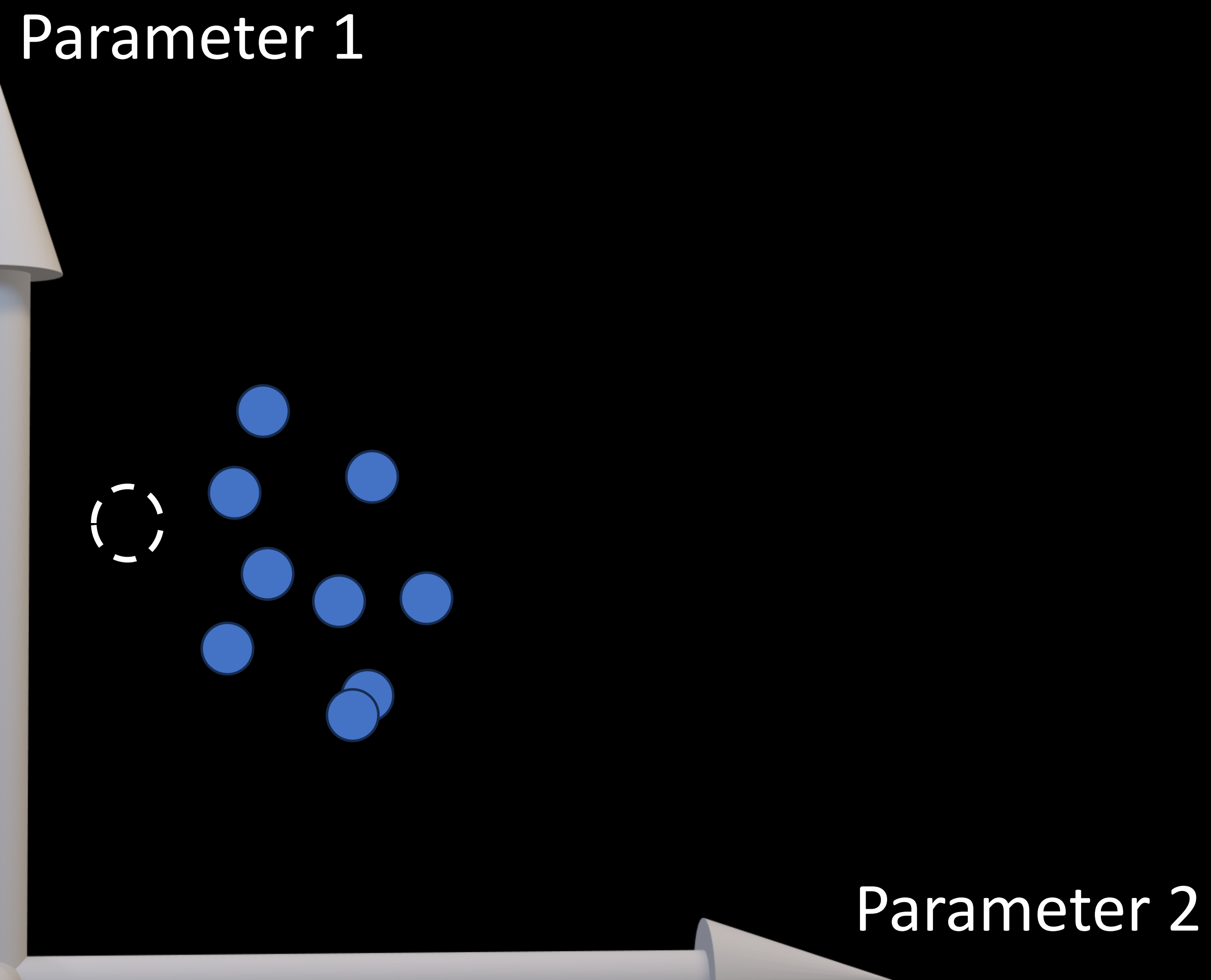
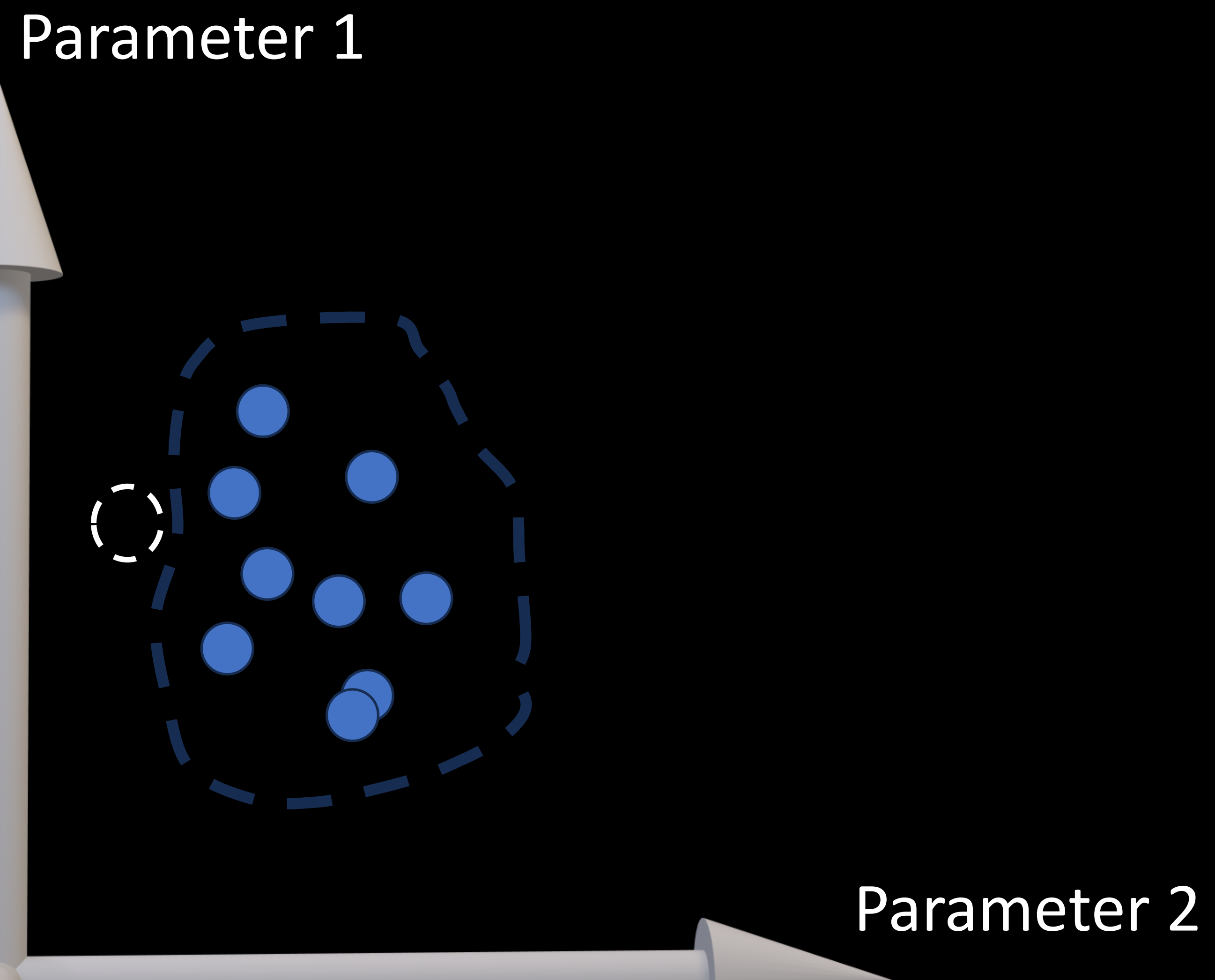
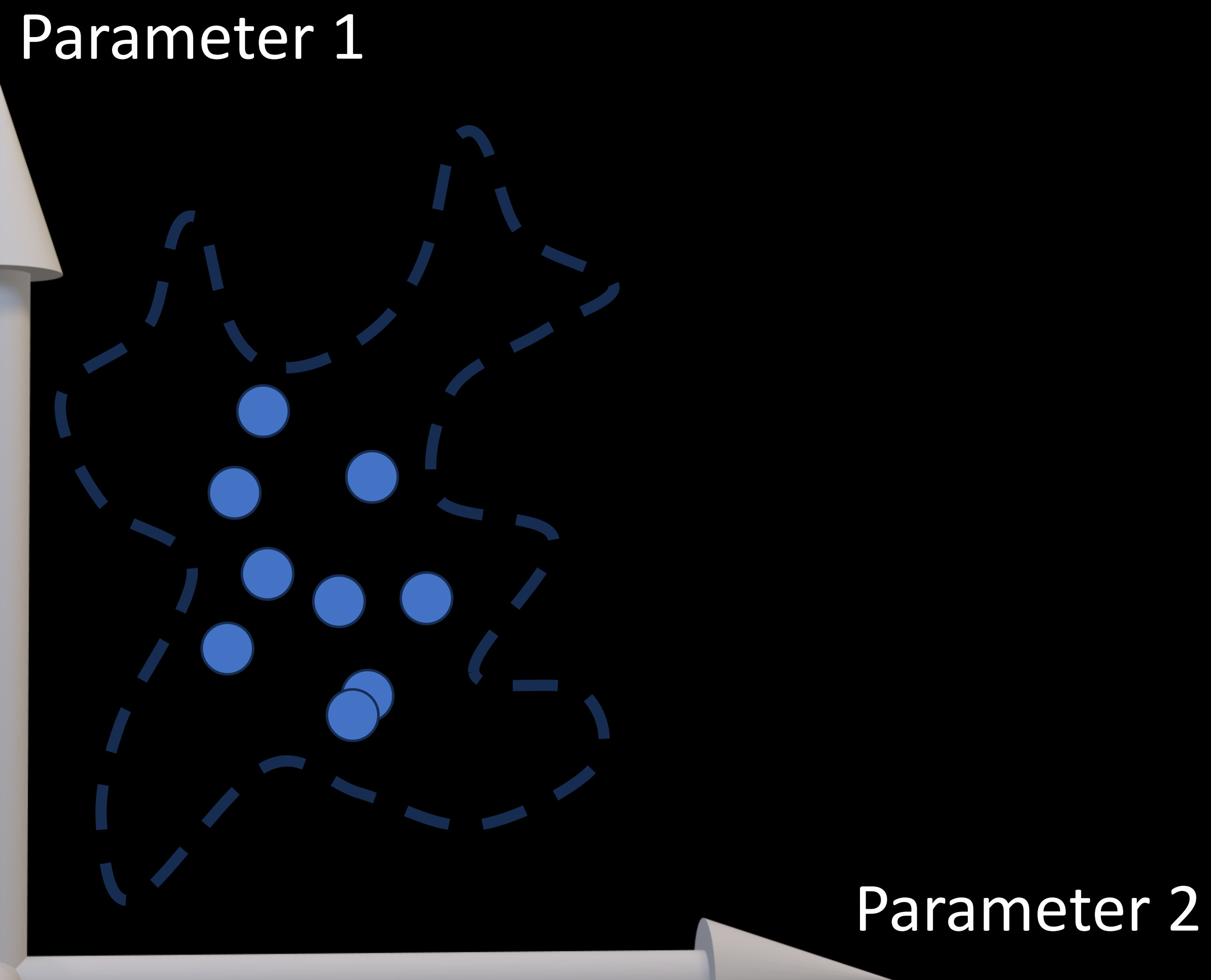


Generation from the Latent Space



Generation from the Latent Space



Universal Approximation Theorem (UAT)

A neural network with at least one hidden layer and a sufficient number of neurons can approximate any continuous function with arbitrary precision, provided an appropriate activation function is used.

Limitations of the theorem:

1. **Does not account for training speed**
2. **Ensures existence, but not construction**
3. **A single hidden layer may be inefficient**

- Cybenko, G. Approximation by superpositions of a sigmoidal function. *Math. Control Signal Systems* **2**, 303–314 (1989). https://doi.org/10.1007/BF02551274
- **Hornik, K., Stinchcombe, M., & White, H.** Multilayer feedforward networks are universal approximators. *Neural Networks* **2**, 359–366 (1989). https://doi.org/10.1016/0893-6080(89)90020-8
- Funahashi, K.-I. On the approximate realization of continuous mappings by neural networks. Neural Networks 2, 183–192 (1989). https://doi.org/10.1016/0893-6080(89)90003-8

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Image → Latent Space → Image

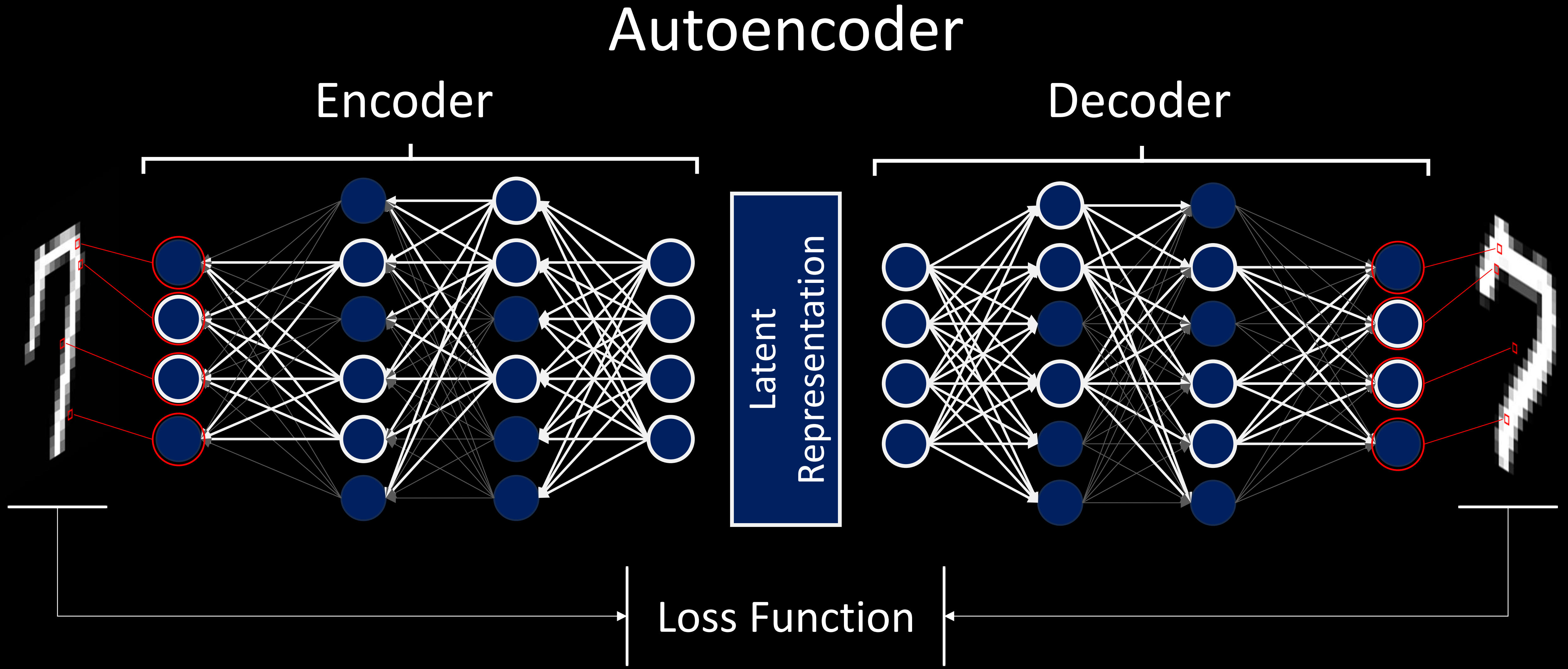
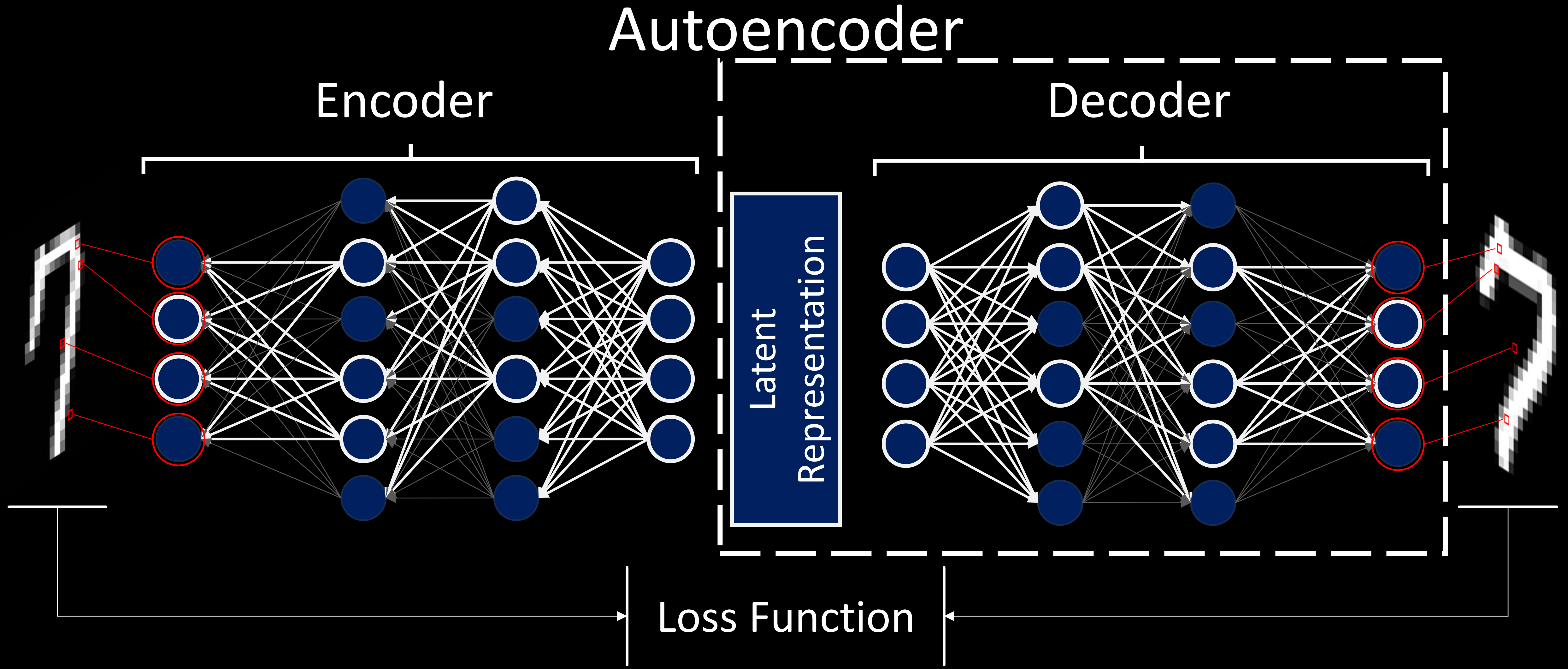
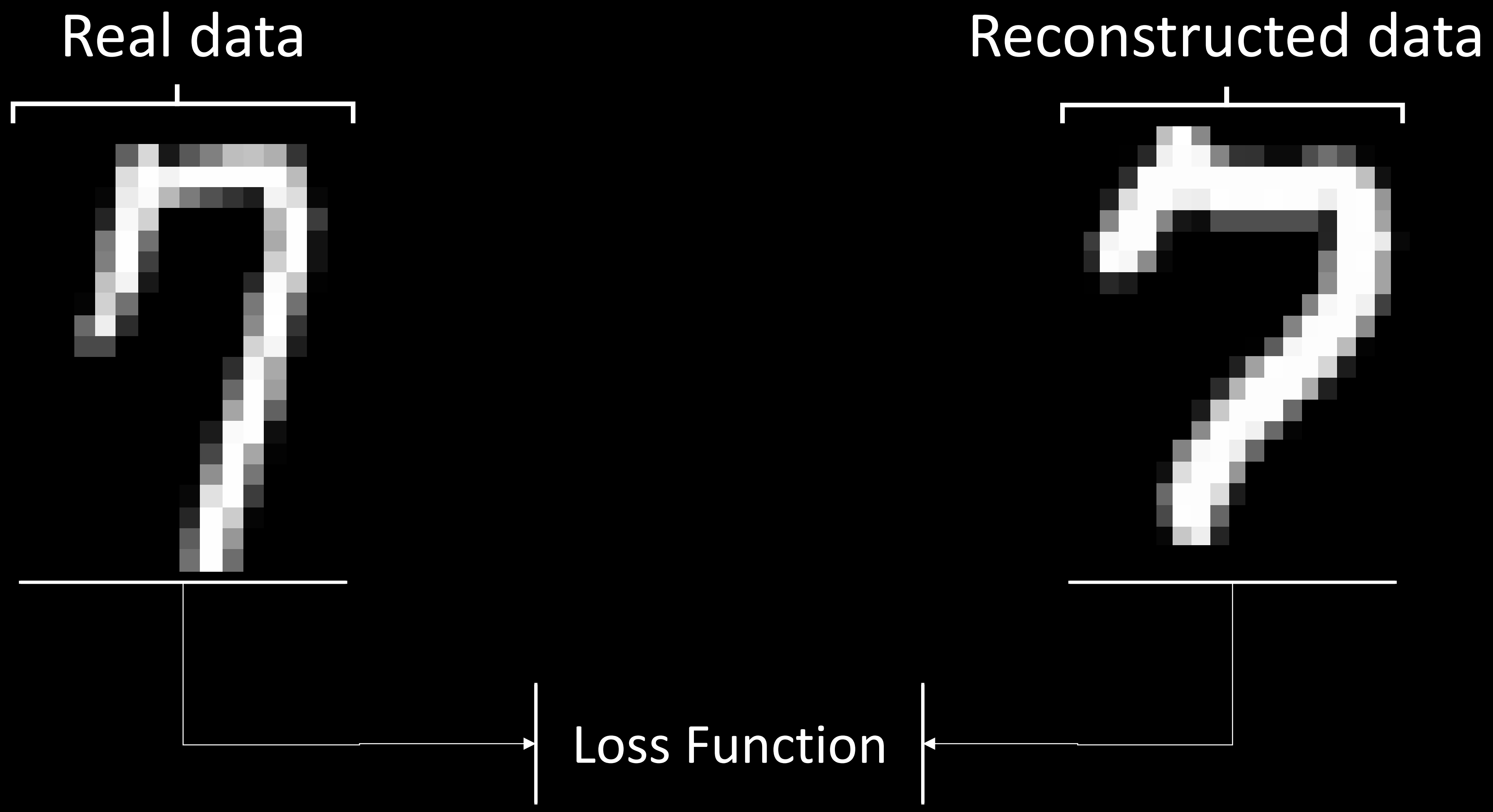


Image → Latent Space → Image



Loss Function for Images



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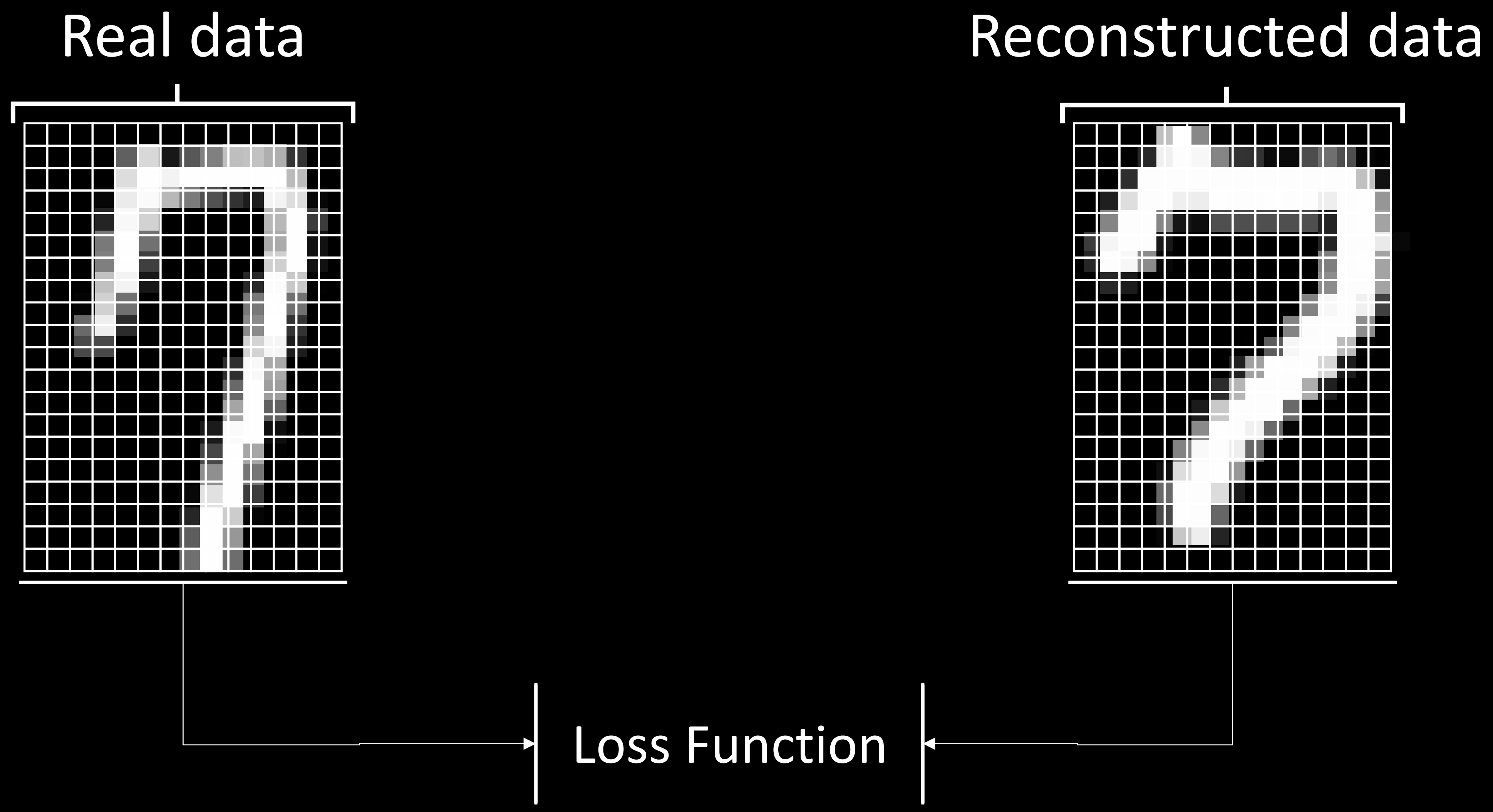
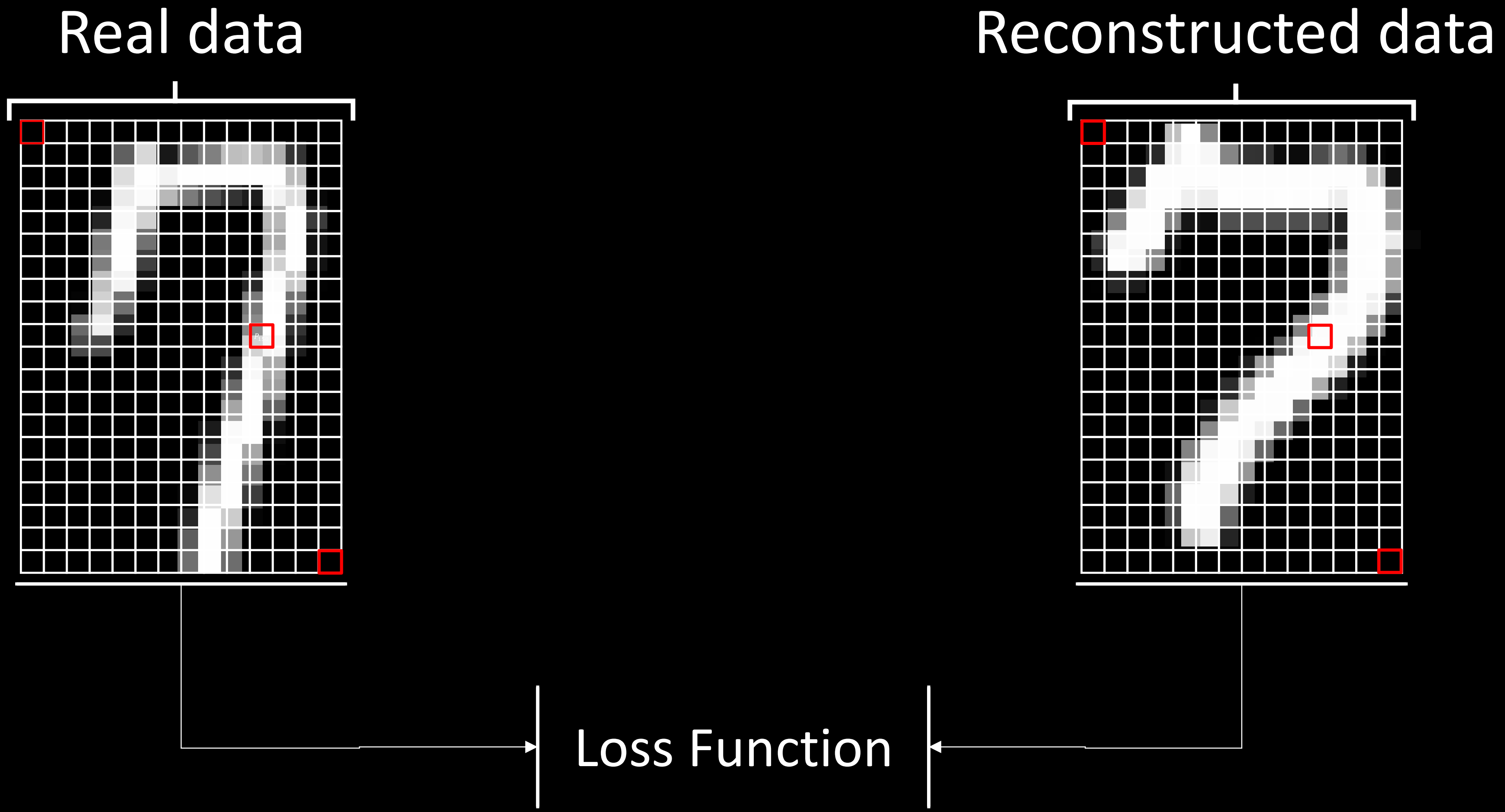
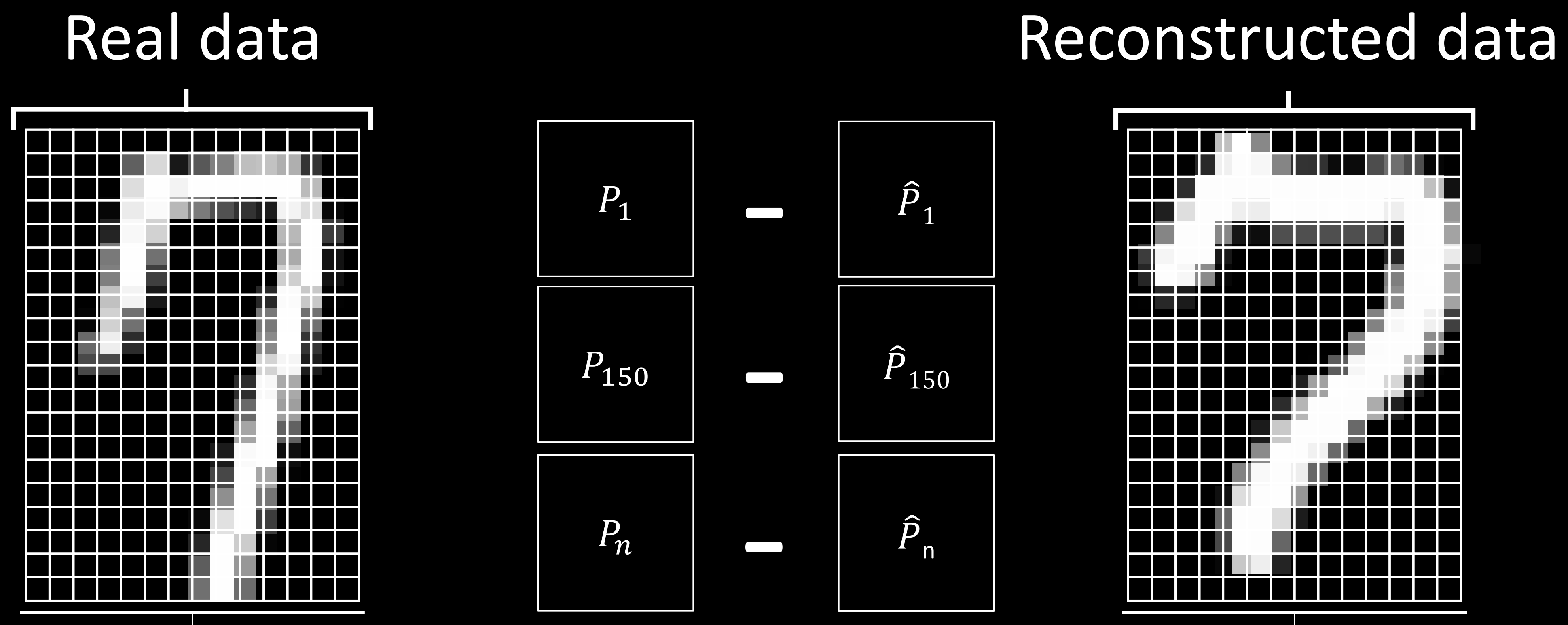


Loss Function for Images



Loss Function for Images



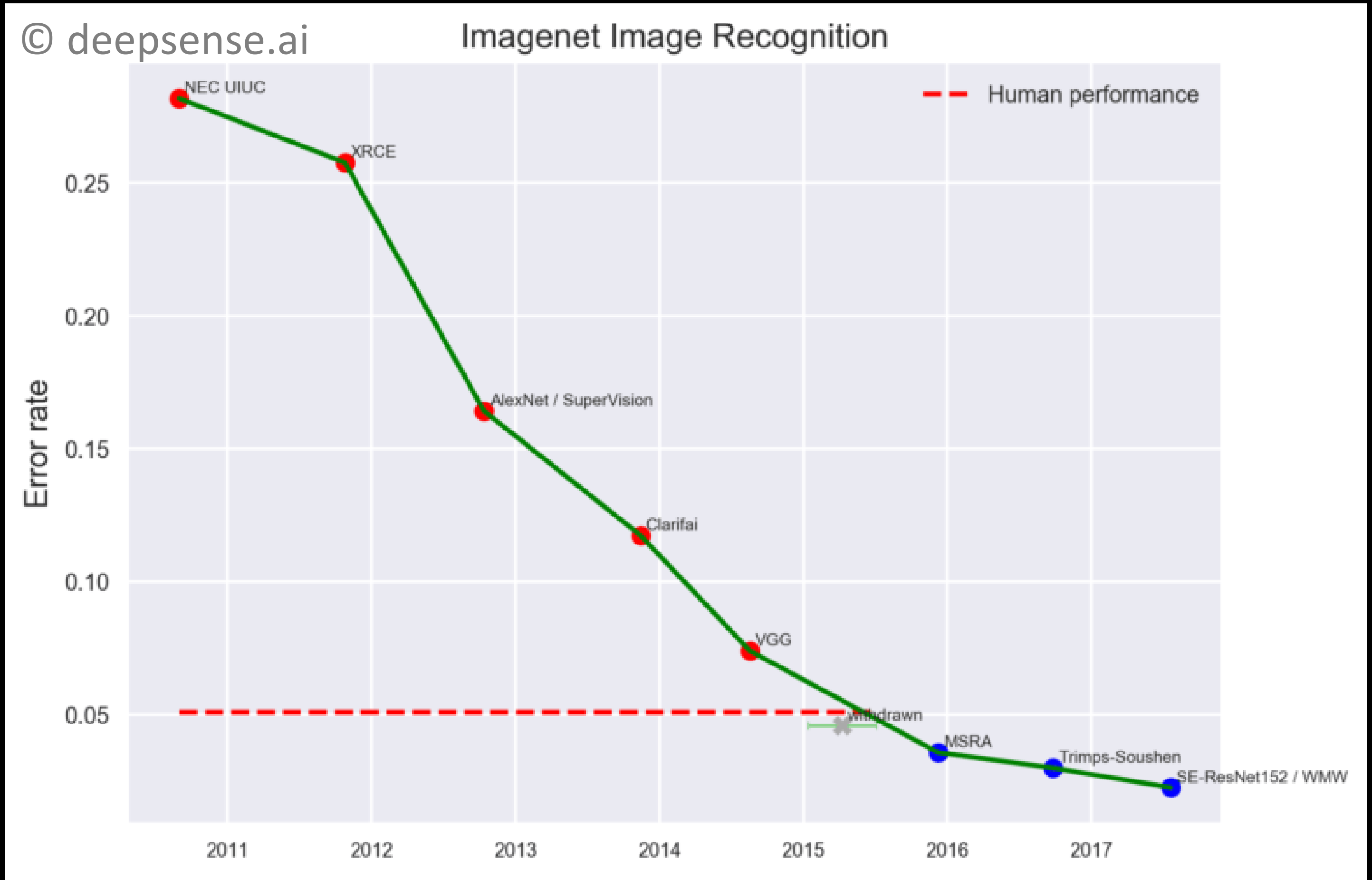
$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(P_i - \hat{P_i}\right)^2$$

Image Blurring Due to MSE Optimization

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(P_i - \widehat{P_i}\right)^2$$

ImageNet Large Scale Visual Recognition Challenge (ILSVRC)

ImageNet Image Catalog
(14,000,000 images, 20,000 classes)



Error Rate Curve of Classifiers
(---- average error rate for humans)

The Original GAN Paper

Generative Adversarial Nets

Ian J. Goodfellow, Jean Pouget-Abadie,* Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair,† Aaron Courville, Yoshua Bengio‡
Département d'informatique et de recherche opérationnelle
Université de Montréal
Montréal, QC H3C 3J7

[stat.ML] 10 Jun 2014

Abstract

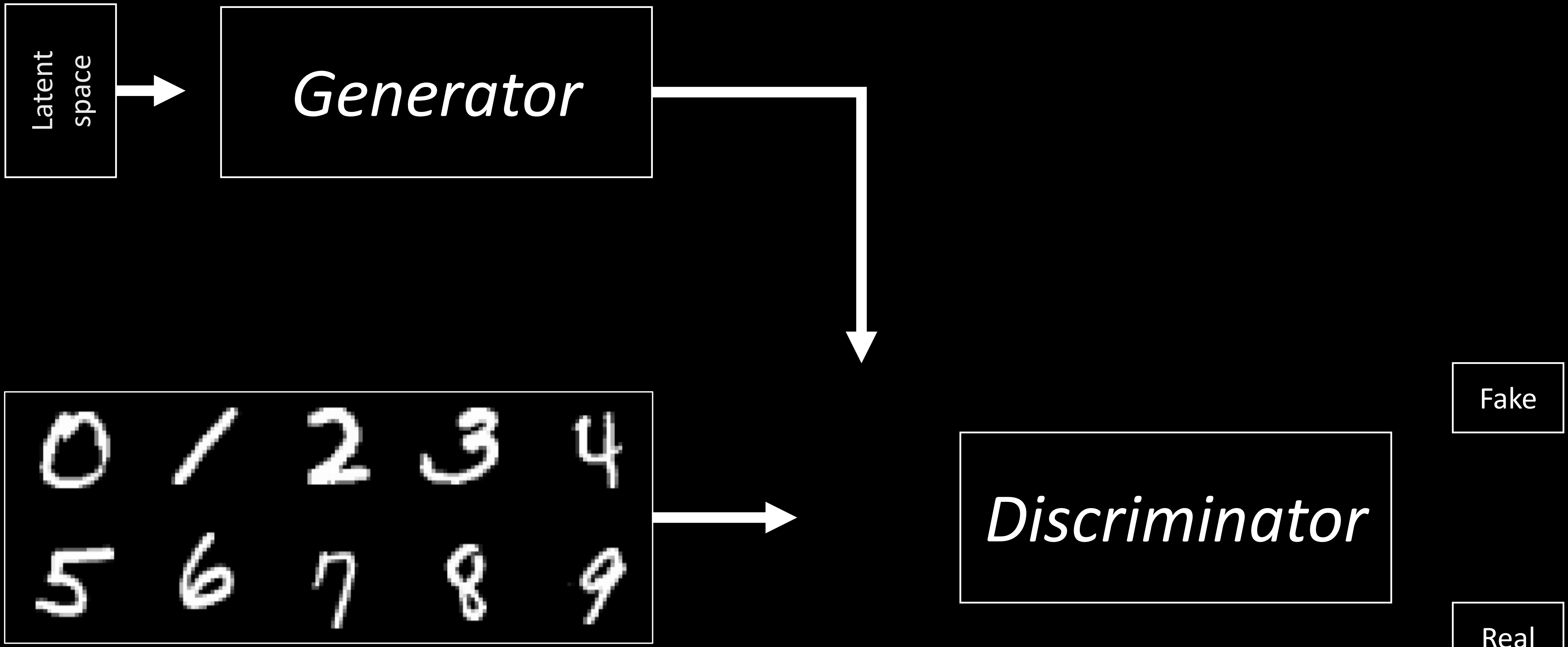
We propose a new framework for estimating generative models via an adversarial process, in which we simultaneously train two models: a generative model G that captures the data distribution, and a discriminative model D that estimates the probability that a sample came from the training data rather than G. The training procedure for G is to maximize the probability of D making a mistake. This framework corresponds to a minimax two-player game. In the space of arbitrary functions G and D, a unique solution exists, with G recovering the training data distribution and D equal to $\frac{1}{2}$ everywhere. In the case where G and D are defined by multilayer perceptrons, the entire system can be trained with backpropagation. There is no need for any Markov chains or unrolled approximate inference networks during either training or generation of samples. Experiments demonstrate the potential of the framework through qualitative and quantitative evaluation of the generated samples.

Generator

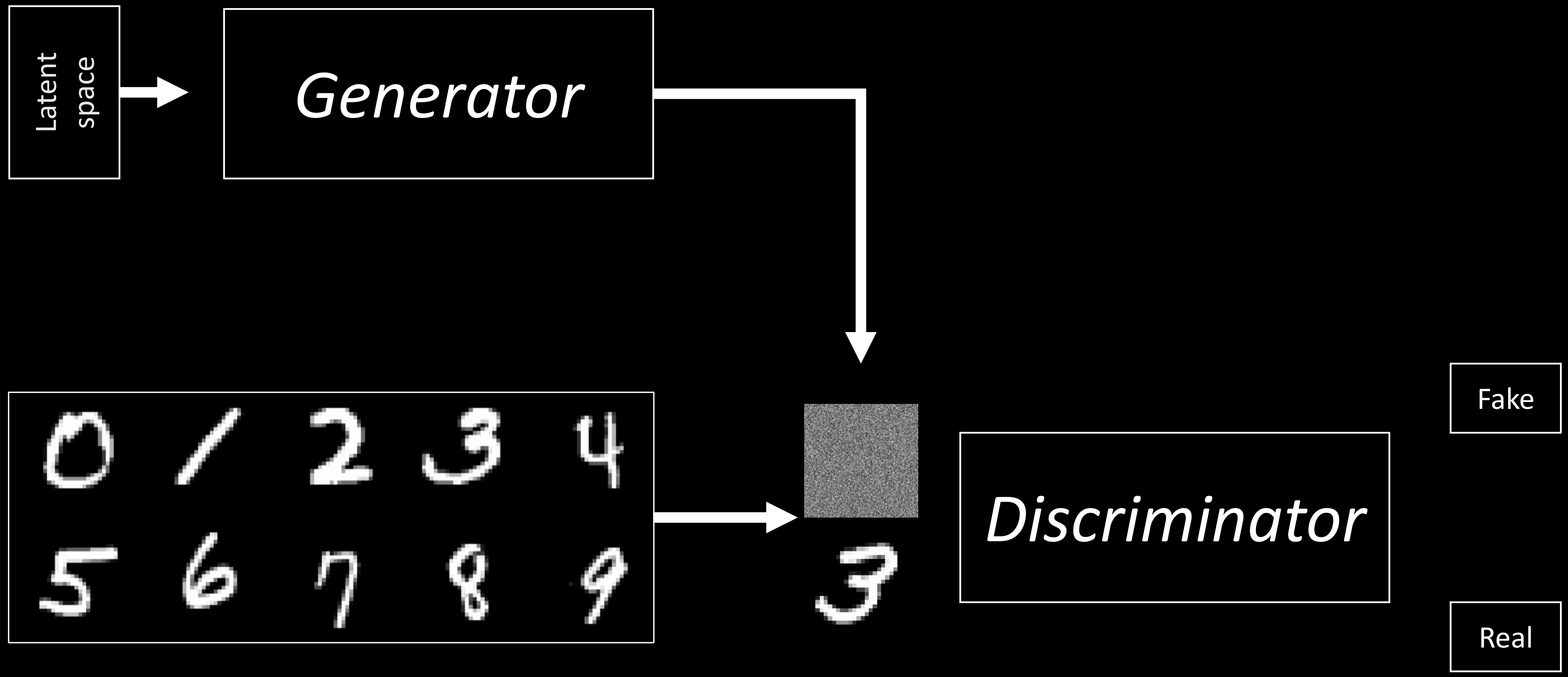
Discriminator

Goodfellow, I. J., Pouget-Abadie, J., Mirza, M., et al. Generative adversarial networks. *arXiv preprint* (2014). https://doi.org/10.48550/arXiv.1406.2661

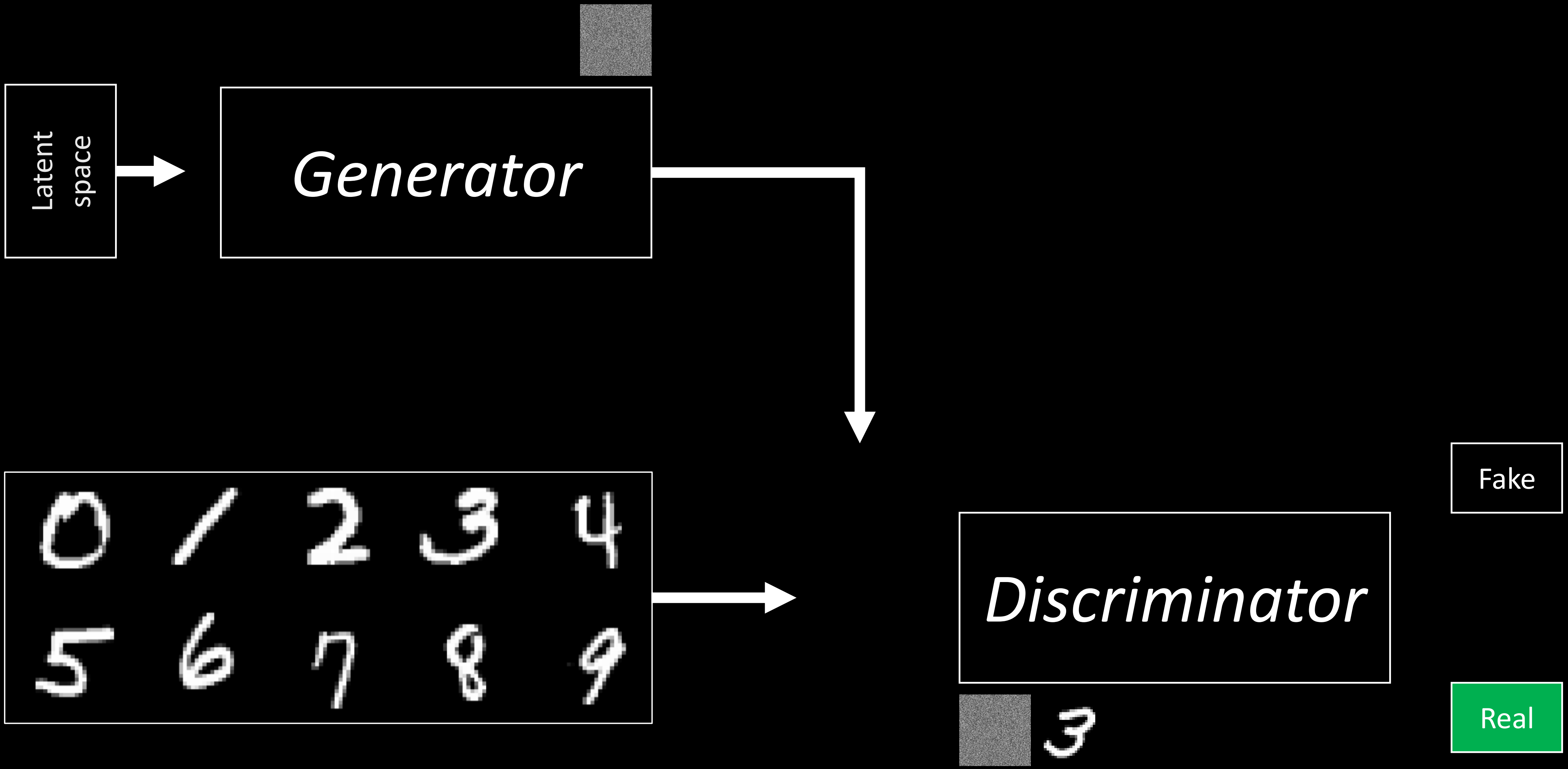
GAN Architecture



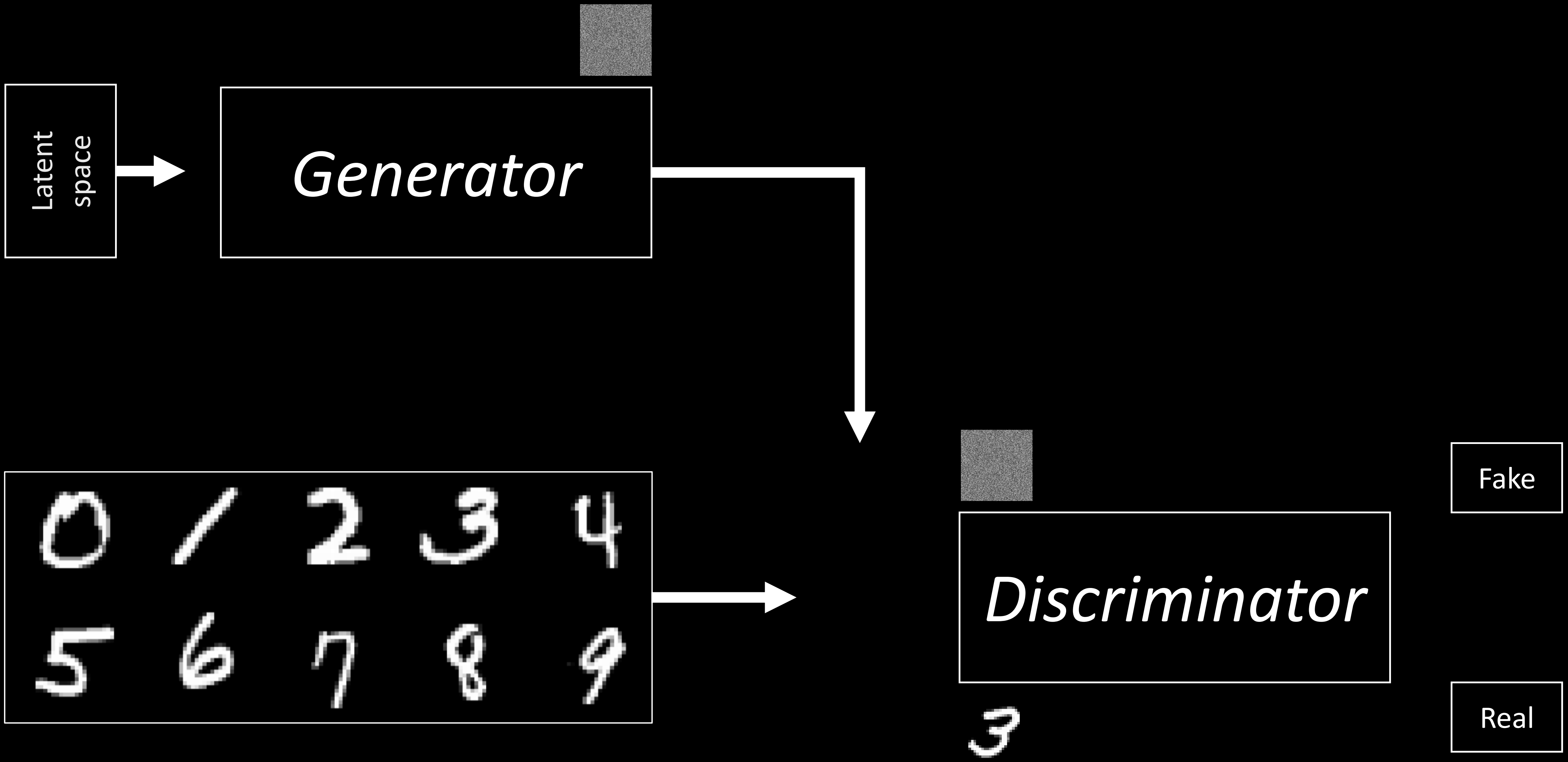
GAN Architecture



GAN Architecture



GAN Architecture



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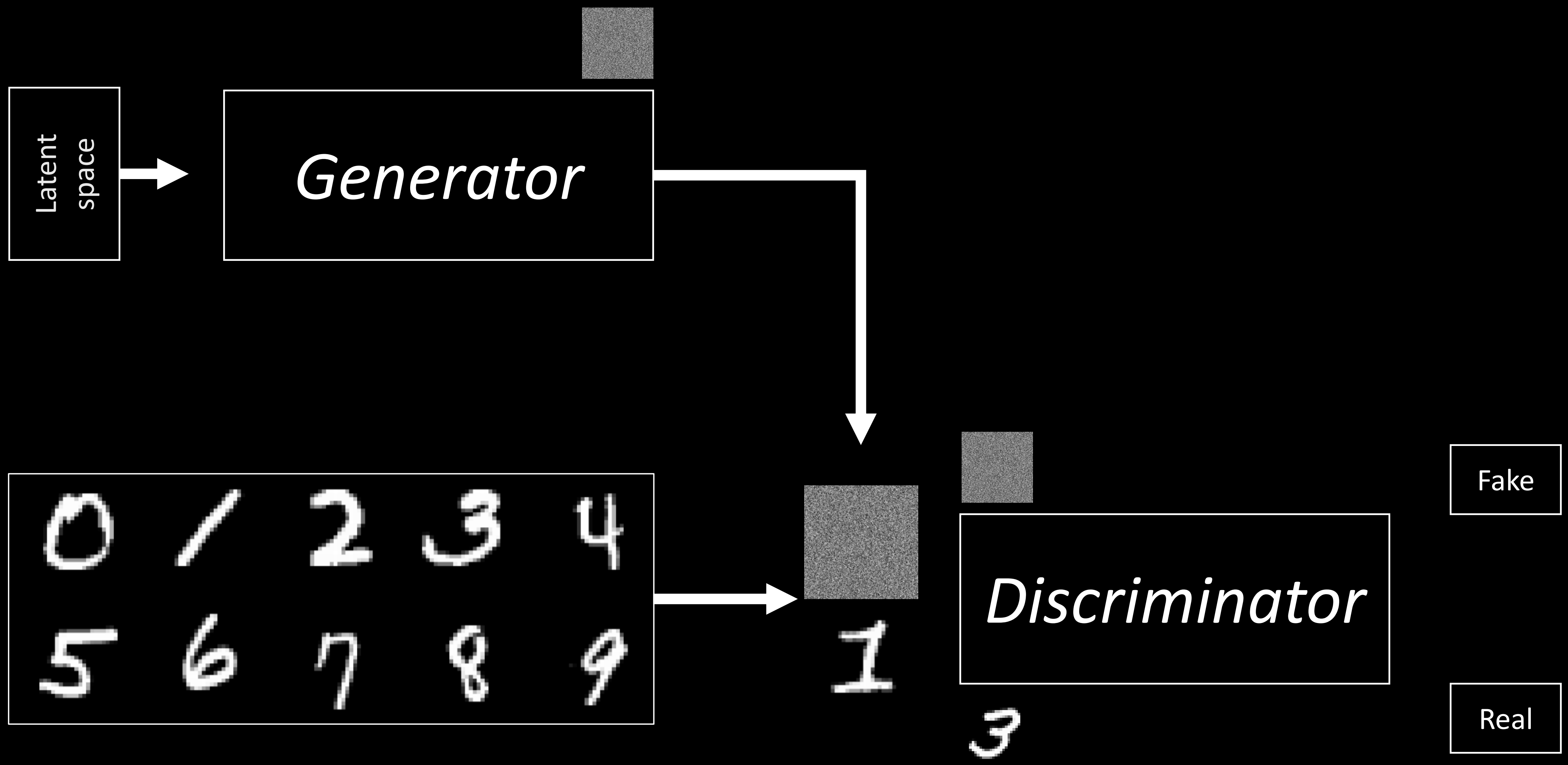
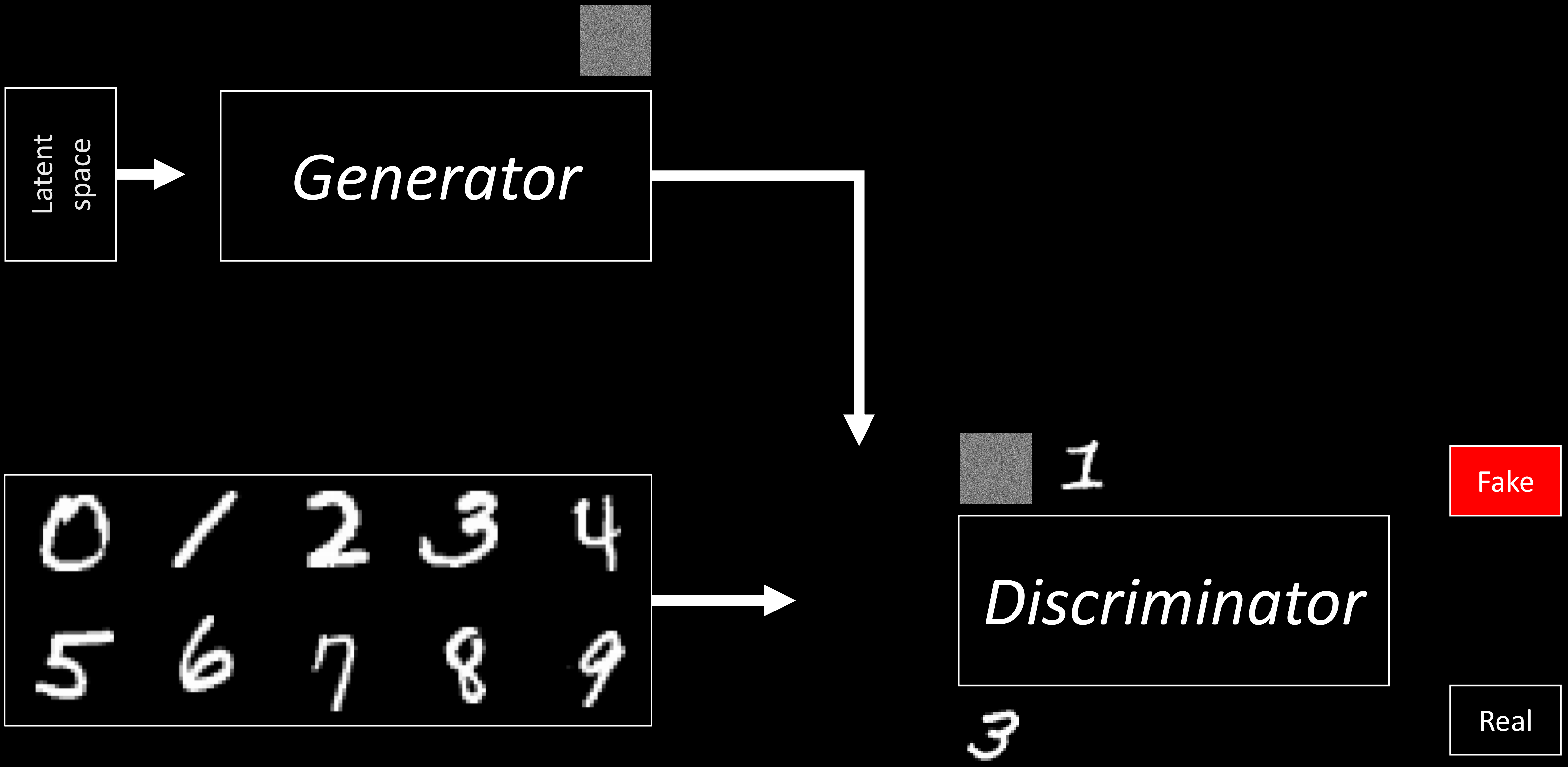
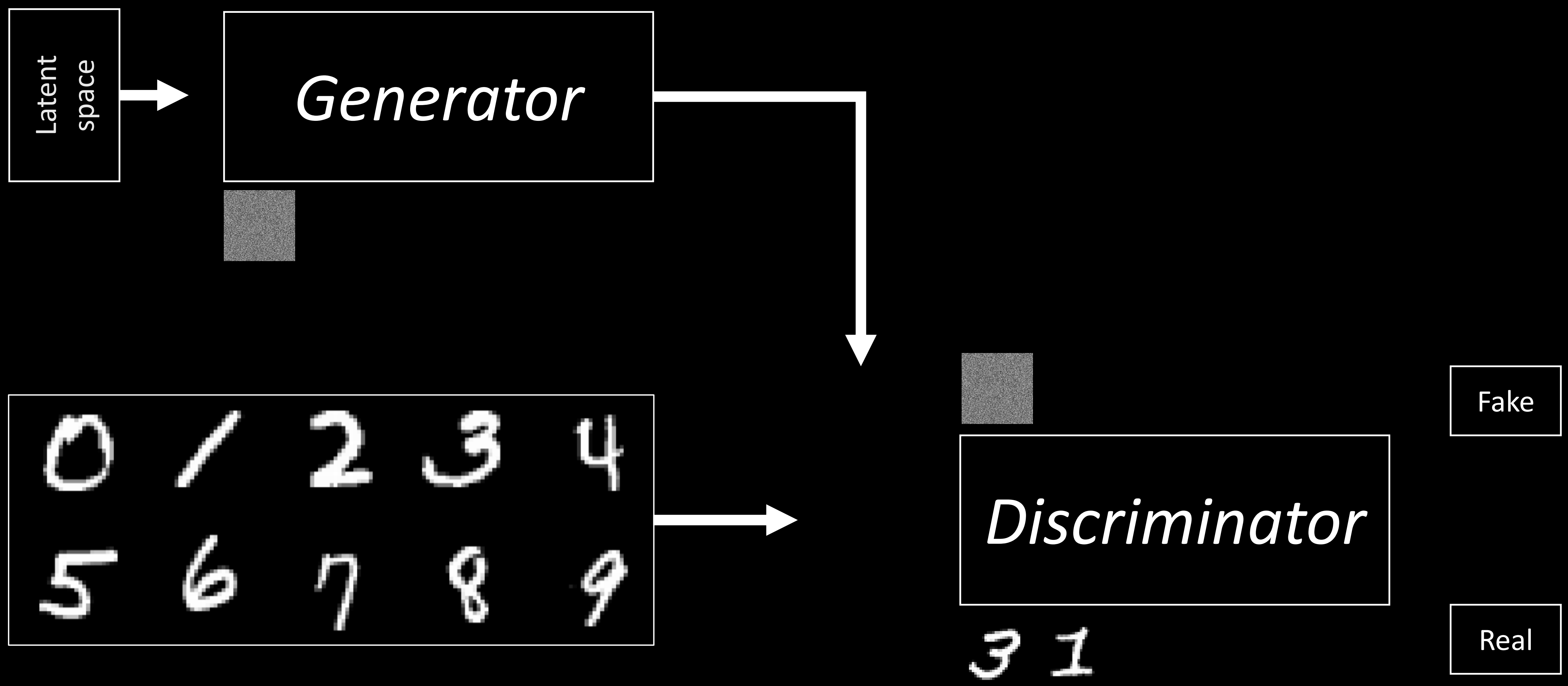


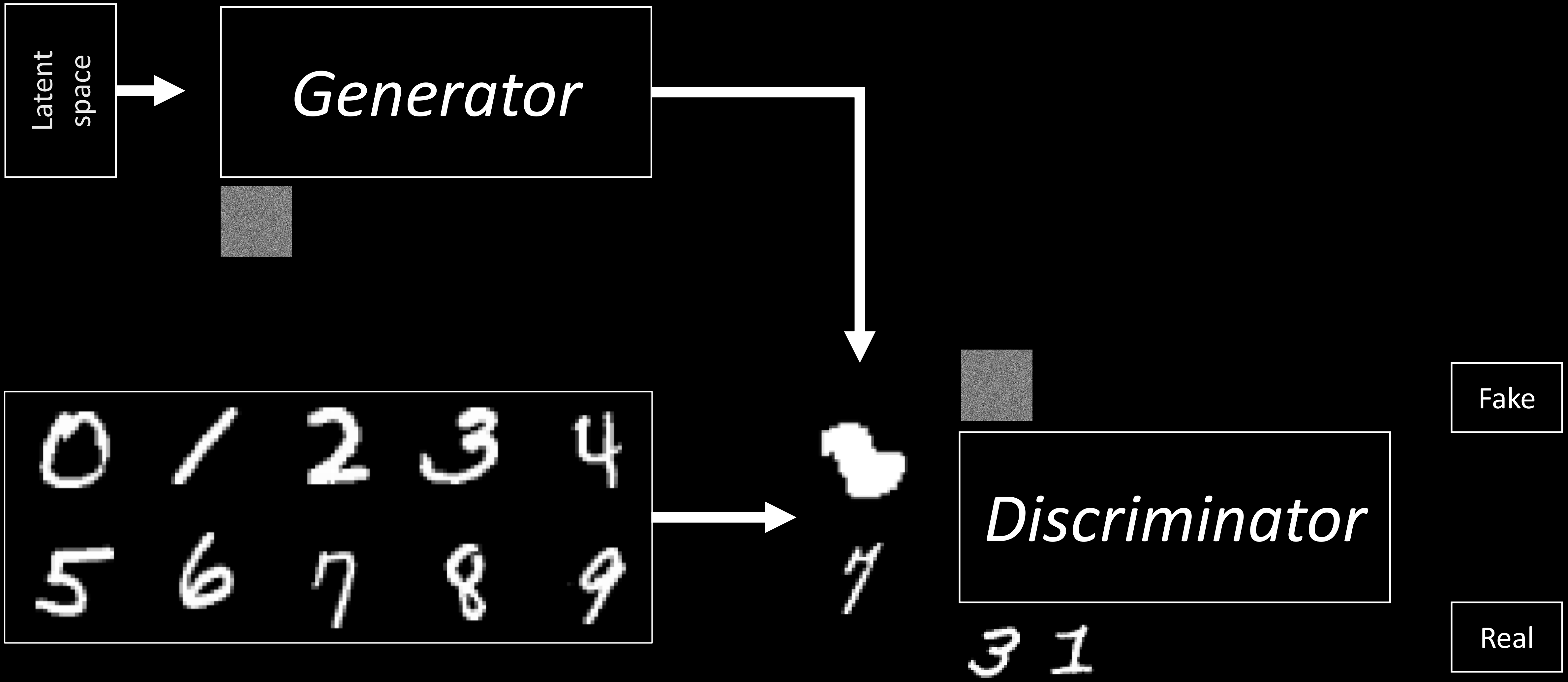
GAN Architecture



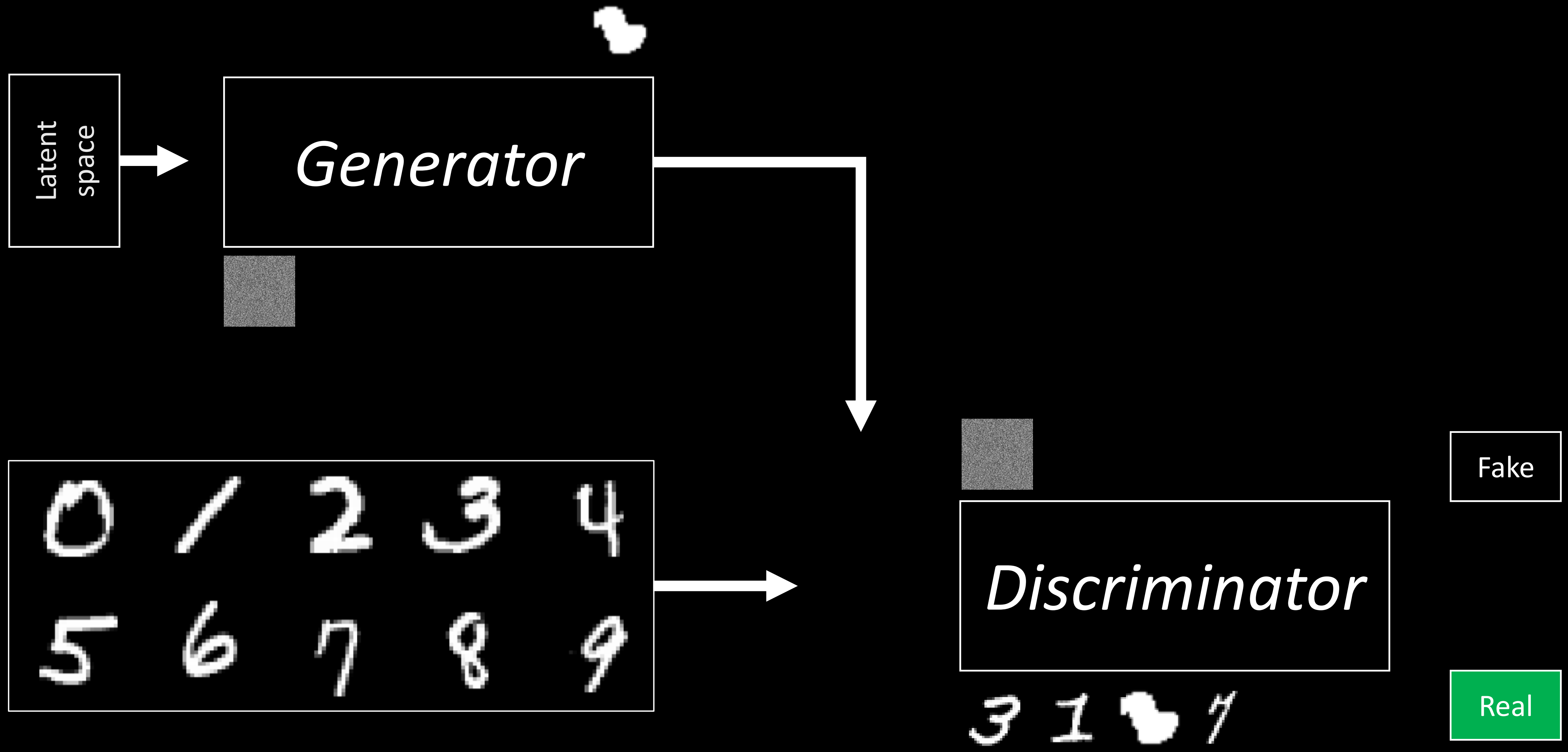
GAN Architecture



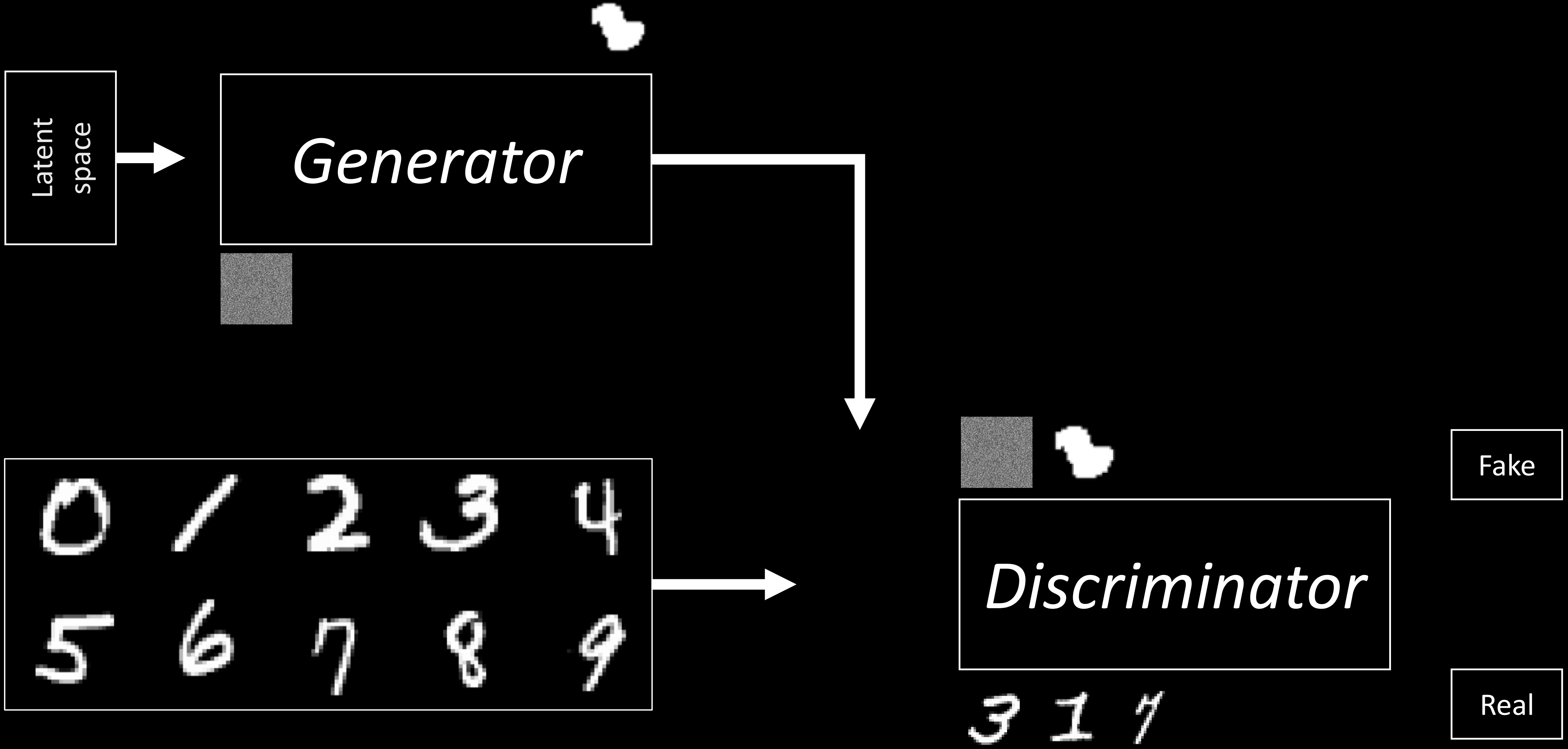
GAN Architecture



GAN Architecture



GAN Architecture



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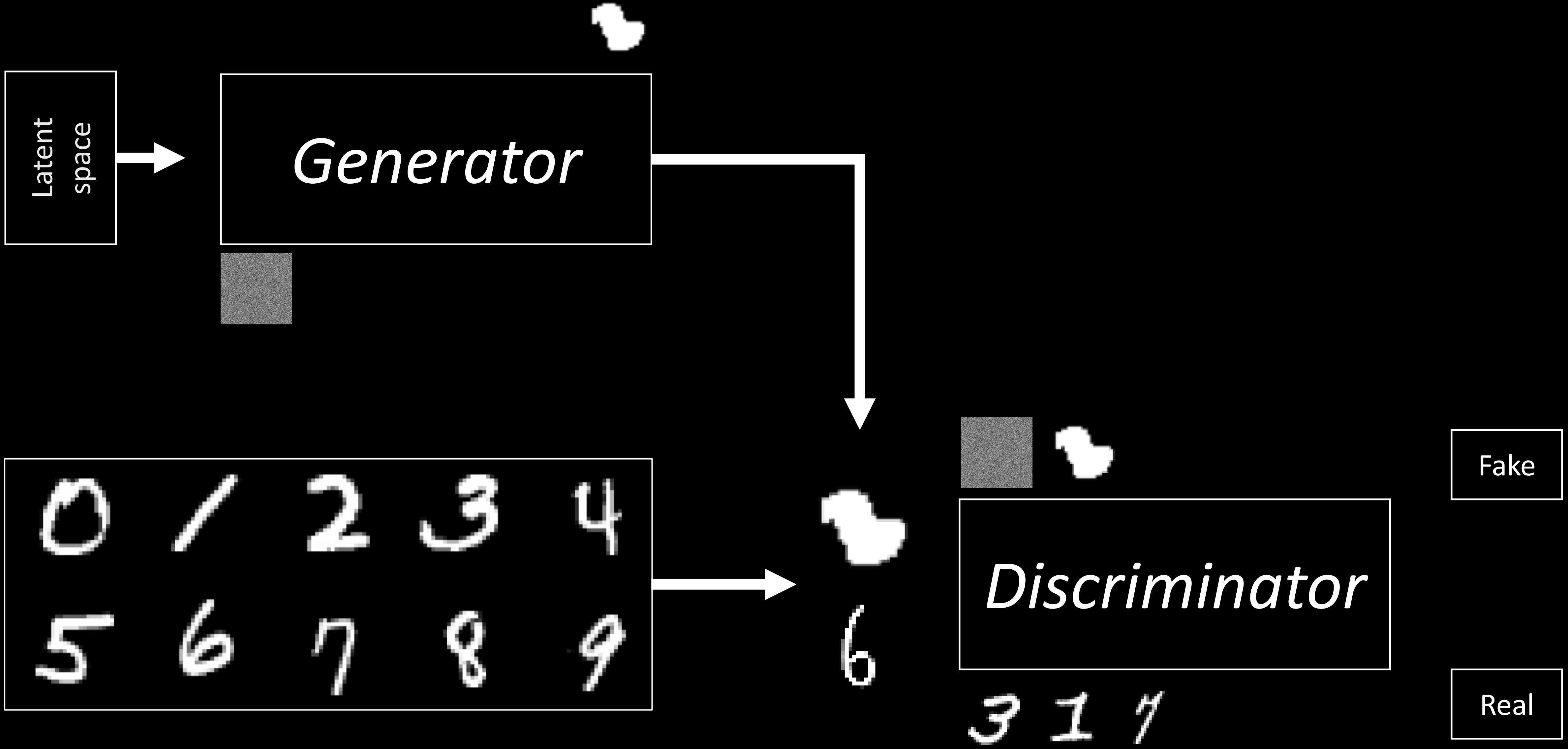

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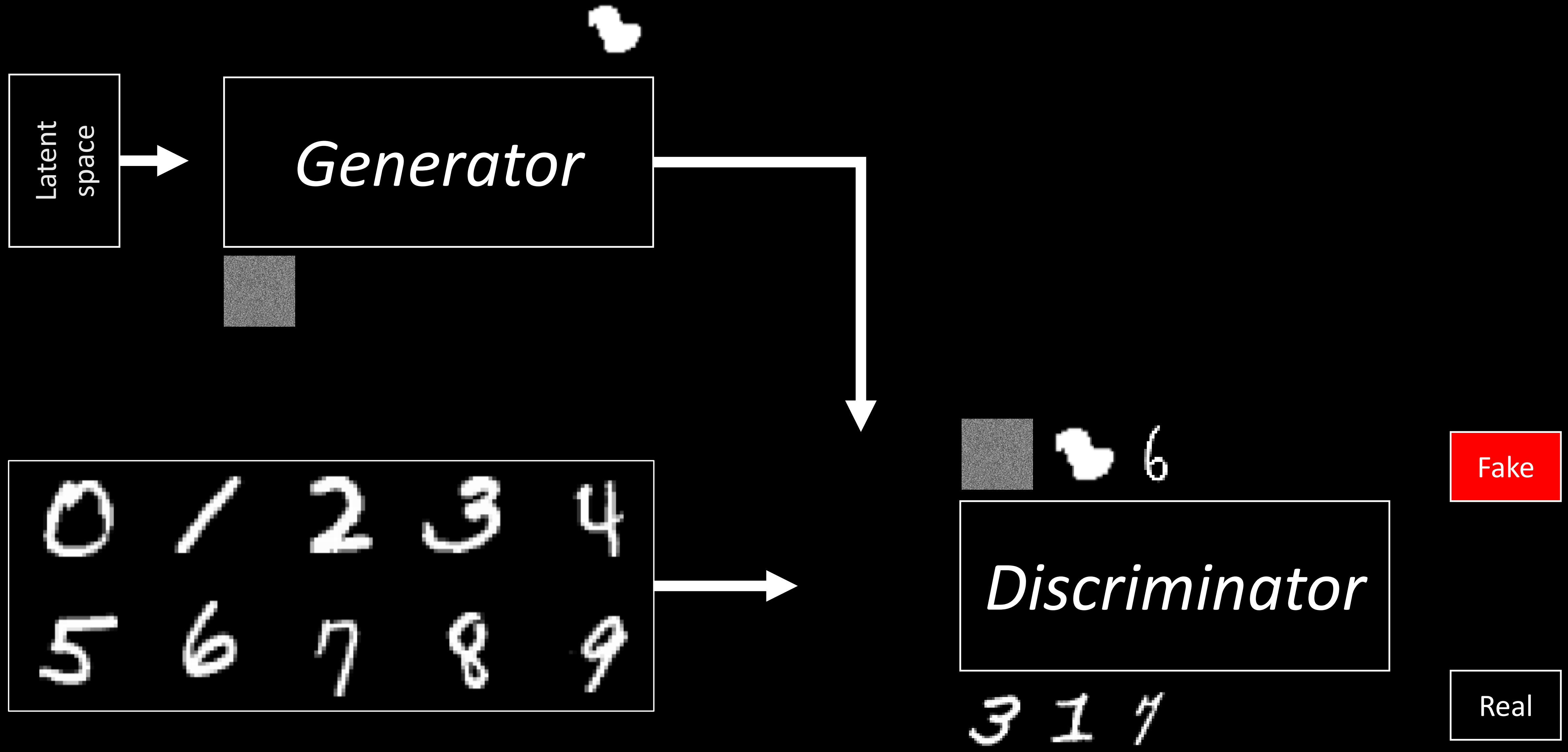

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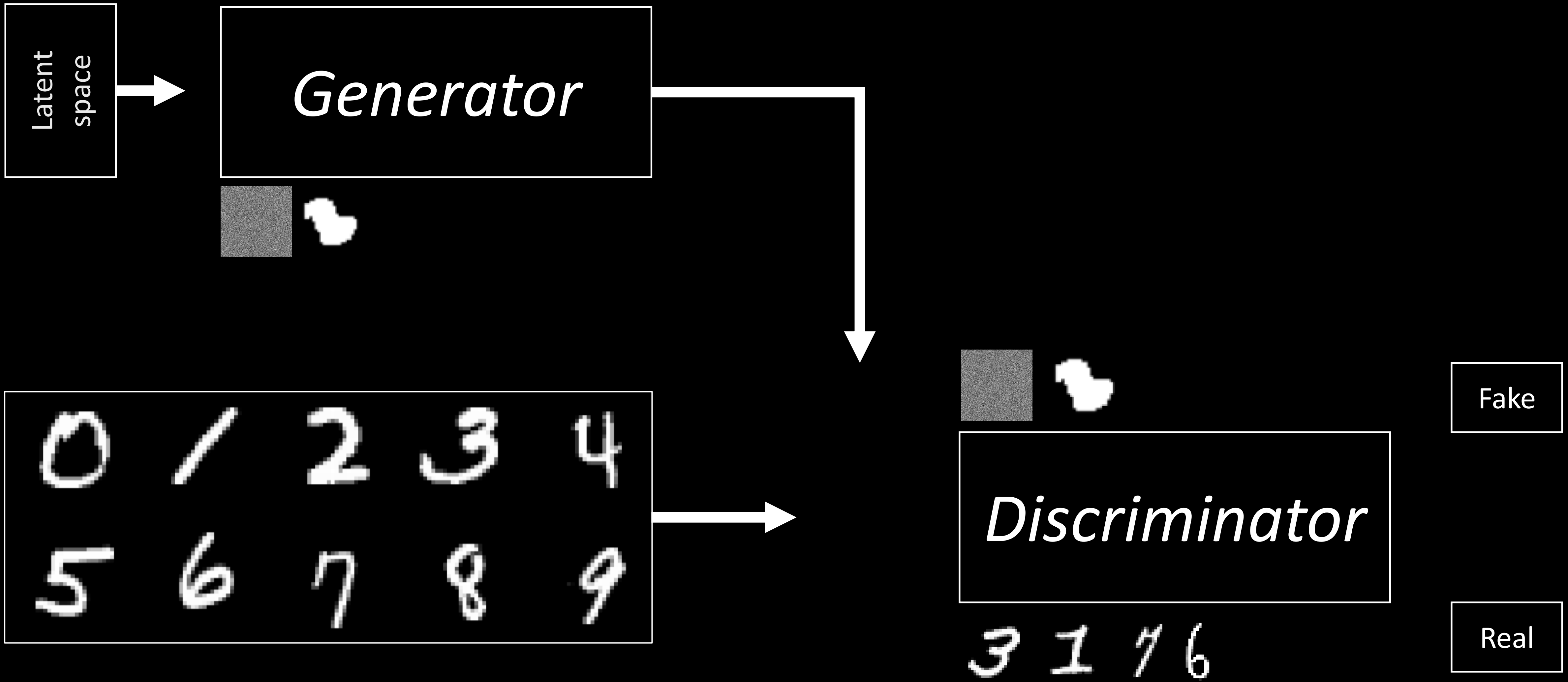

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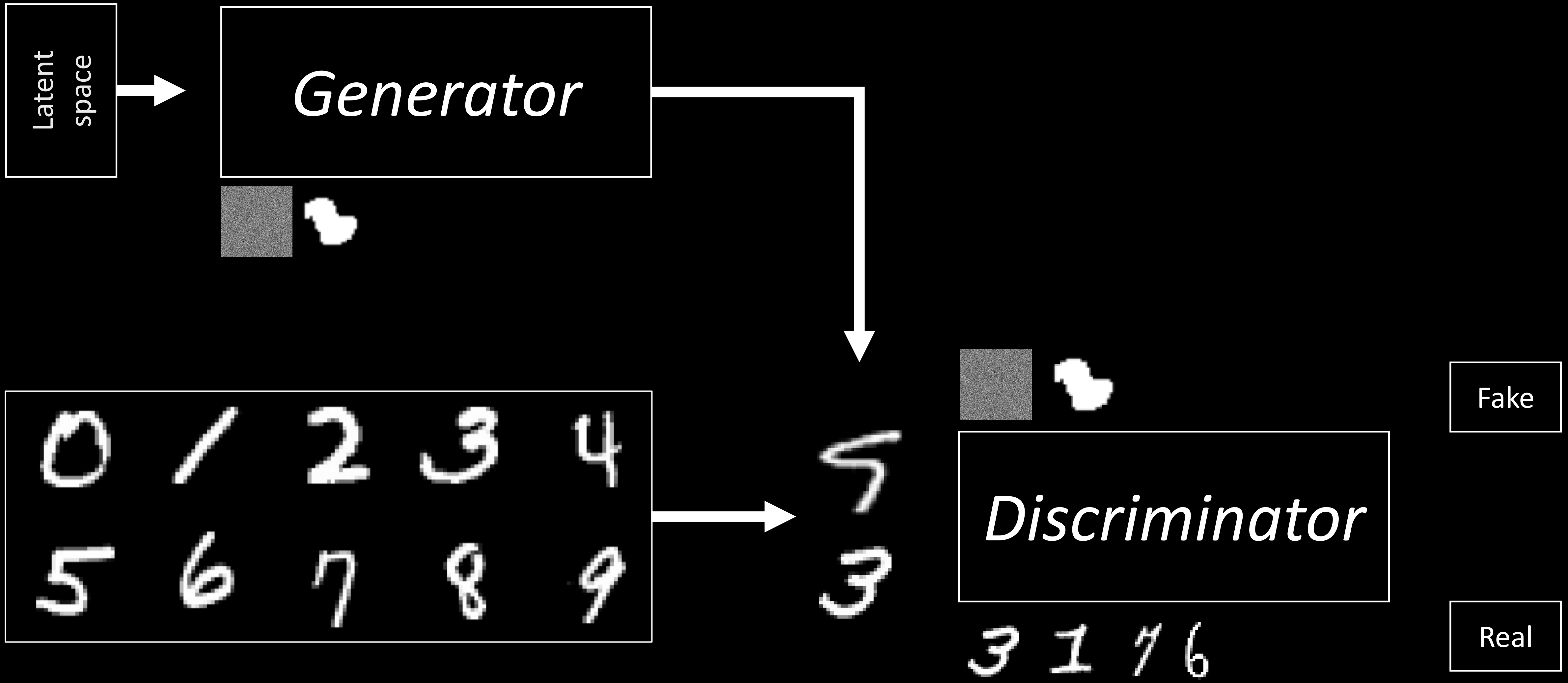
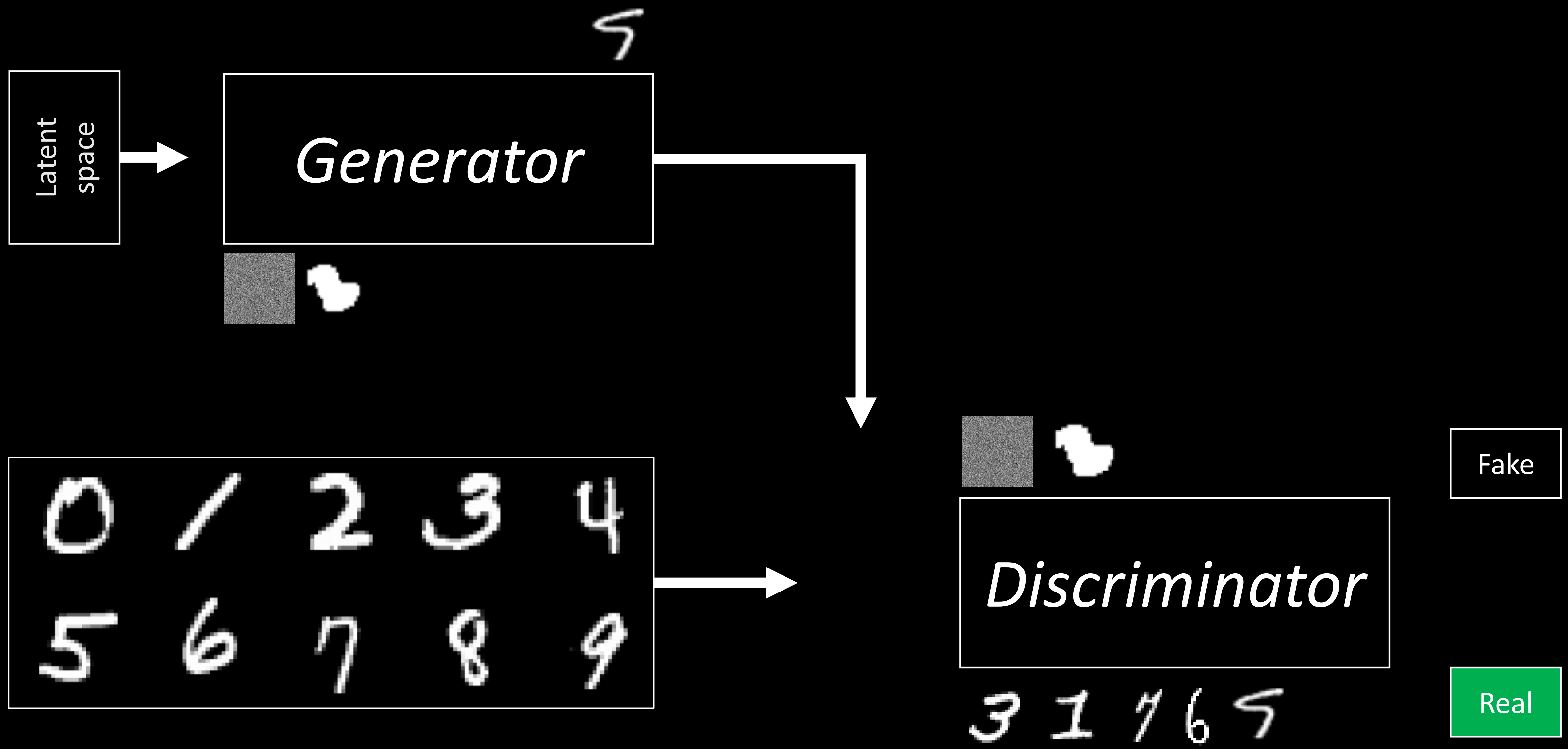


GAN Architecture



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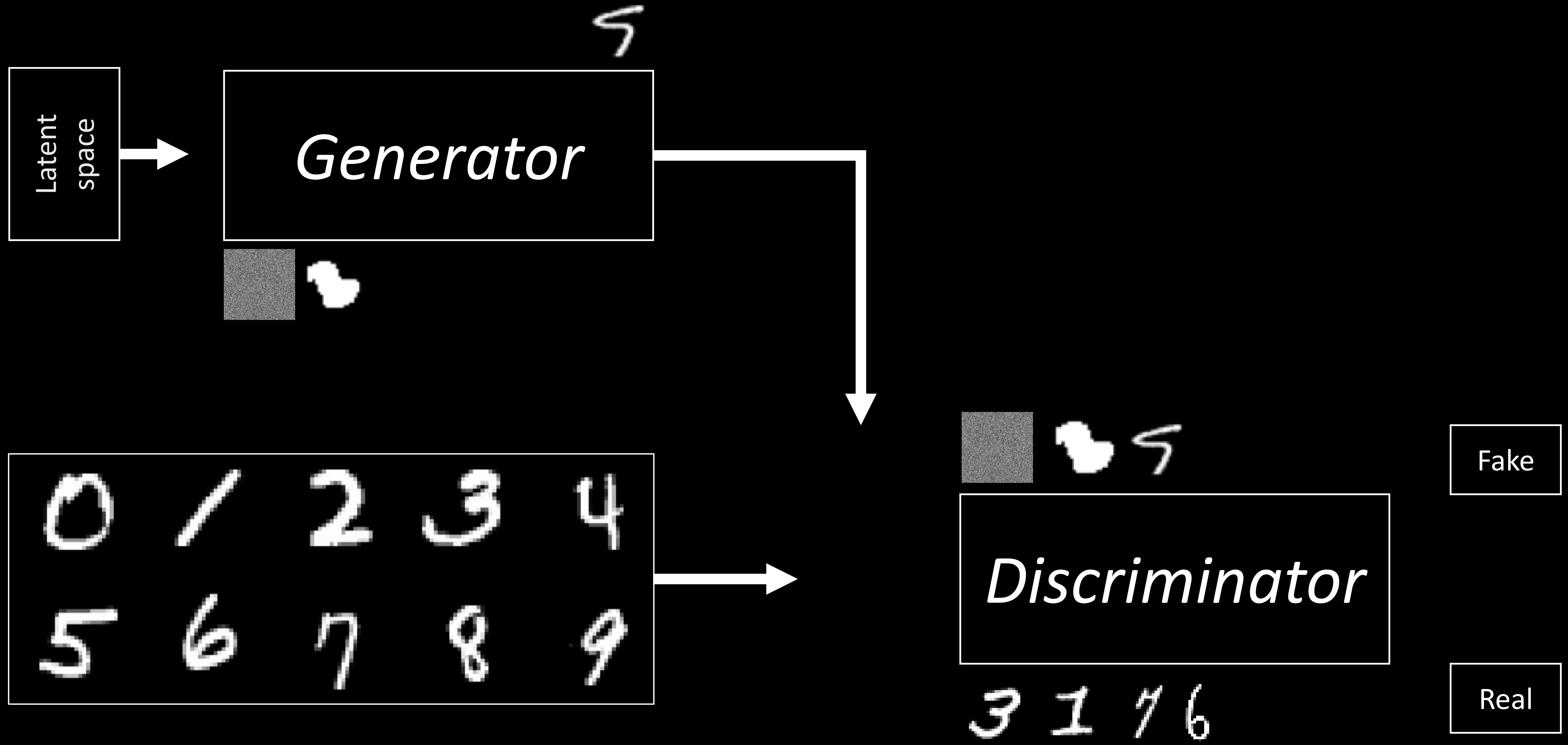

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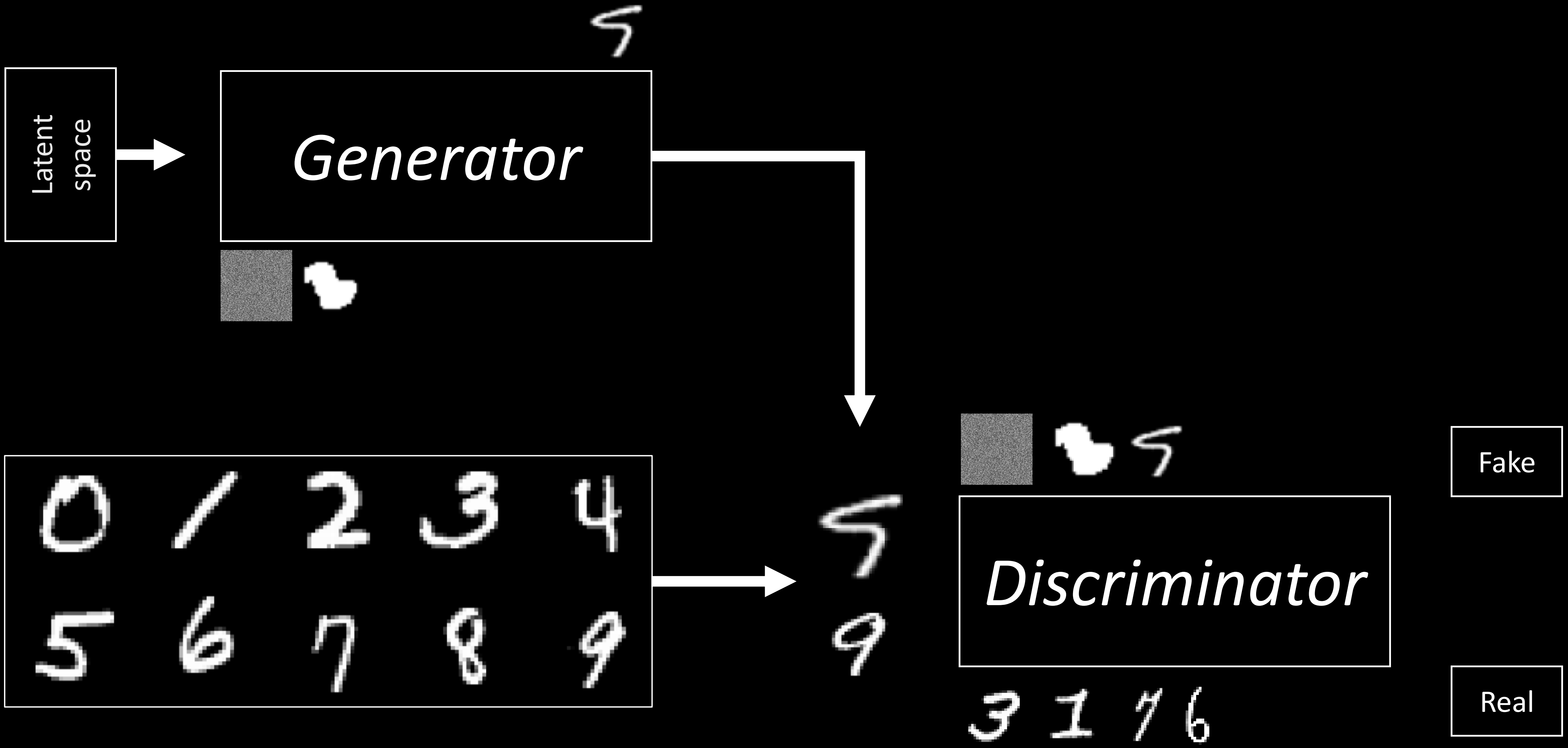

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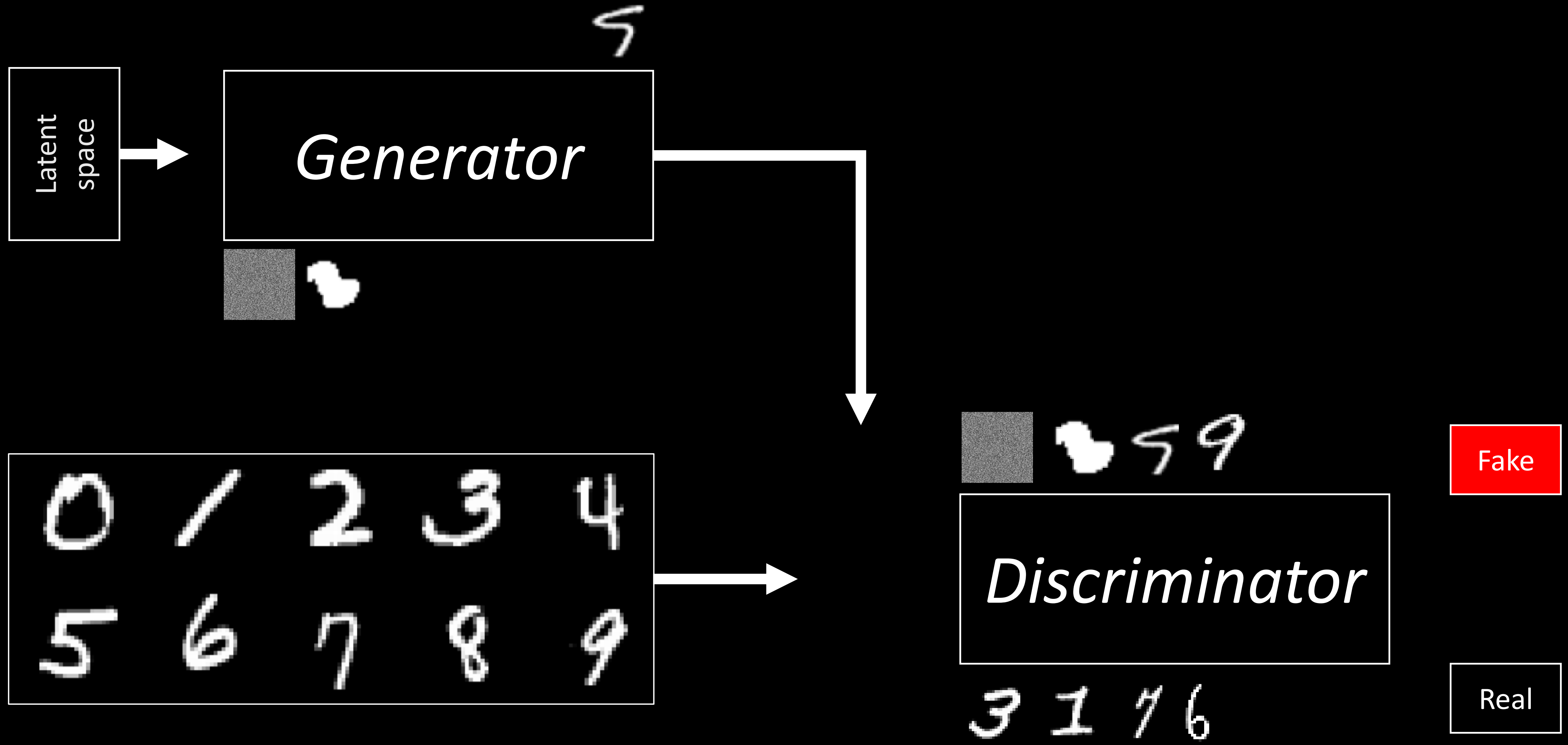

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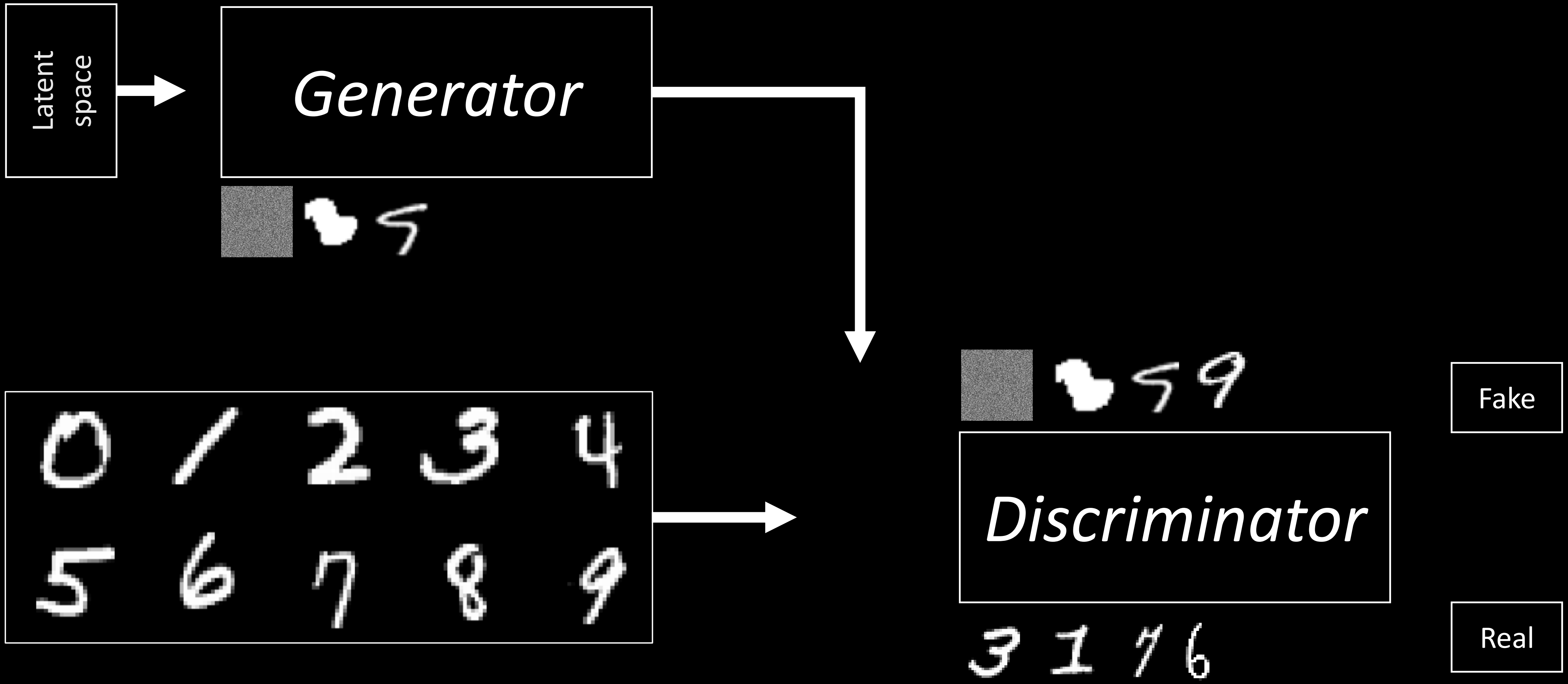
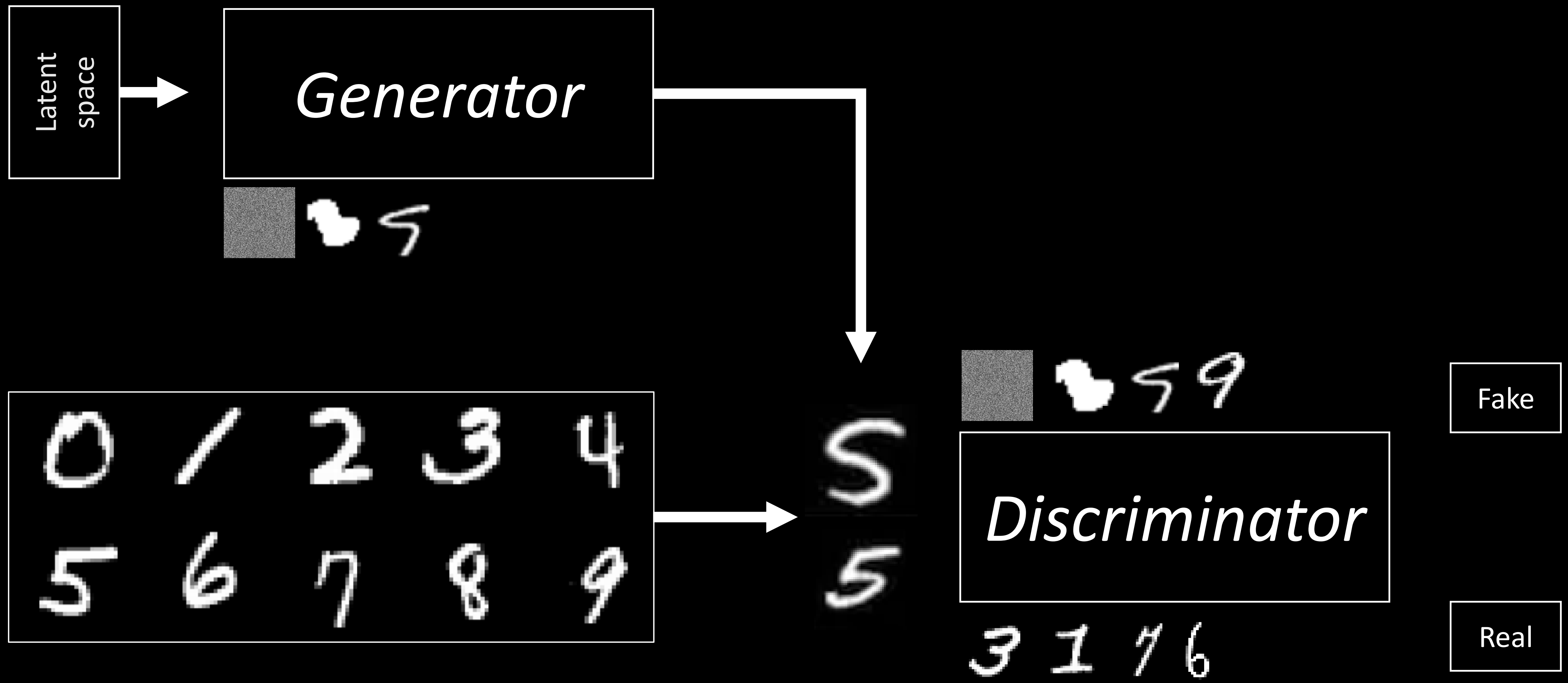


GAN Architecture



GAN Principle

Generator	*Discriminator*

Fake

Real

Returns the data generated from the latent space

Returns the probability that the data is real

It has never seen any real data

It learns from real data

It strives to decrease D efficiency

It strives to increase its efficiency

$$\min_G \max_D V(G, D)$$

Adversarial

Generator

Discriminator

$$\min_G \max_D V(G, D)$$

Loss Function for GAN

Binary Cross-Entropy (BCE) is a loss function that measures the difference between predicted probabilities and true labels in a binary classification task.

$$\mathrm{B}CE = -\frac{1}{n}\sum_{i=1}^{n}\left(Y_i \log \widehat{Y_i} + (1 - Y_i) \cdot \log\left(1 - \widehat{Y_i}\right)\right)$$

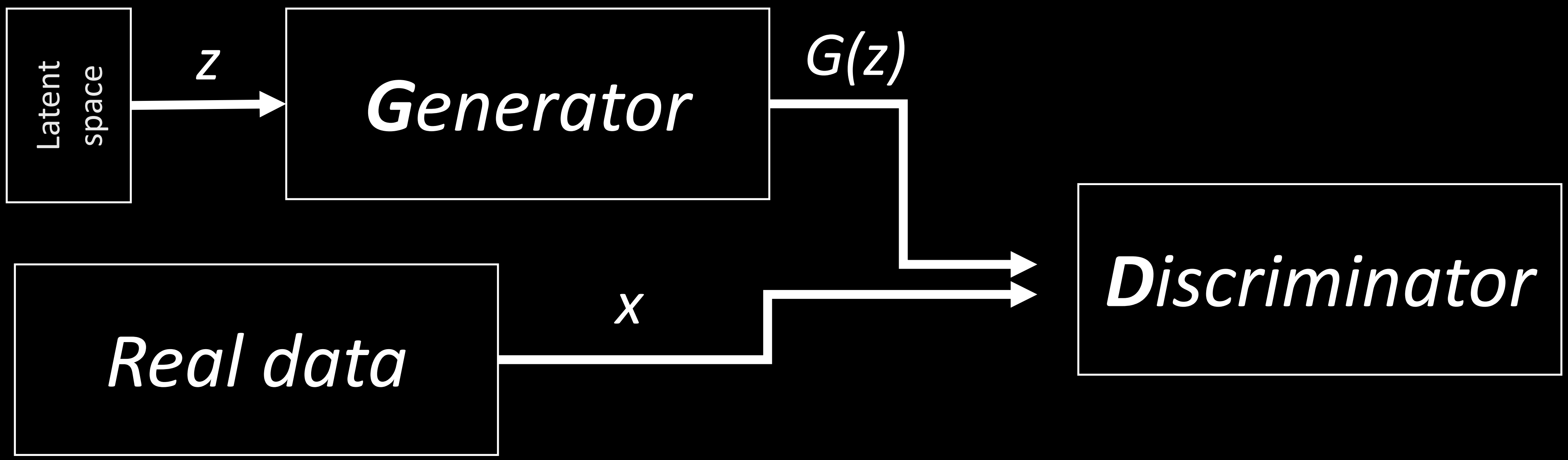
Y_i — the true value for the i-th example (0 or 1)

$\widehat{Y_i}$ — the predicted probability by the model of belonging to class 1 (a value between 0 and 1)

Loss Function for GAN

$$L_D = -\frac{1}{n}\sum_{i=1}^{n}(\log D(x_i) + \log(1 - D(G(z_i))))$$

$$L_G = -\frac{1}{n}\sum_{i=1}^{n}\log(D(G(z_i)))$$



Training Instability

$$w_{new} = w_{old} - \underbrace{\varepsilon}_{\text{Learning rate}} \cdot \nabla L(w_{old})$$

Mode collapse

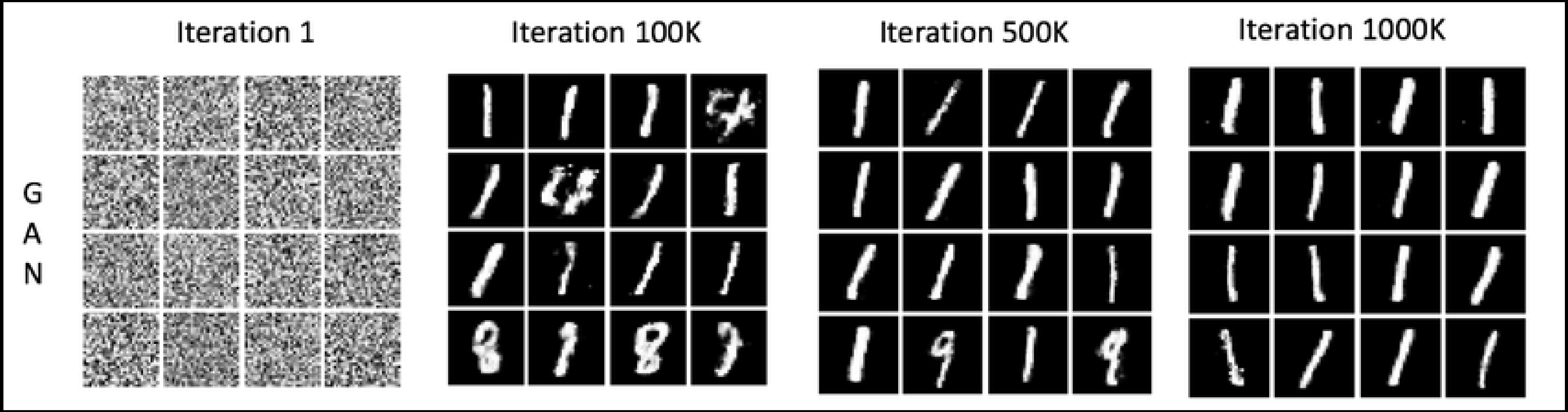


Figure 2 from[1]. Generated images by GAN models trained on MNIST after 1,100k,500k,1000k iterations.

[1]**Mi, L., Shen, M., & Zhang, J.** A probe towards understanding GAN and VAE models. *arXiv preprint* (2018). https://doi.org/10.48550/arXiv.1812.05676

GAN

Super-Resolution GAN

Context-Conditional GAN

Wasserstein GAN

Semi-Supervised GAN

PixelDA

CycleGAN

Conditional GAN

Pix2Pix

Bidirectional GAN

Coupled GANs

GAN

Wasserstein GAN GP

Adversarial Autoencoder

DiscoGAN

Boundary-Seeking GAN

StyleGAN

LSGAN

Context Encoder

Auxiliary Classifier GAN

CycleGANs

VAE-GAN

InfoGAN

DualGAN

Deep Convolutional GAN

StyleGAN2

Super-Resolution GAN

Context-Conditional GAN

Wasserstein GAN

Semi-Supervised GAN

CycleGAN

PixelDA

Conditional GAN

Bidirectional GAN

Pix2Pix

Coupled GANs

Wasserstein GAN GP

GAN

Adversarial Autoencoder

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LSGAN

Context Encoder

Auxiliary Classifier GAN

CycleGANs

VAE-GAN

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Deep Convolutional GAN

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StyleGAN2

Context-Conditional GAN

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DiscoGAN

StyleGAN

Boundary-Seeking GAN

LSGAN

Context Encoder

Auxiliary Classifier GAN

VAE-GAN

CycleGANs

InfoGAN

DualGAN

Deep Convolutional GAN

StyleGAN2

Conditional GAN (cGAN)

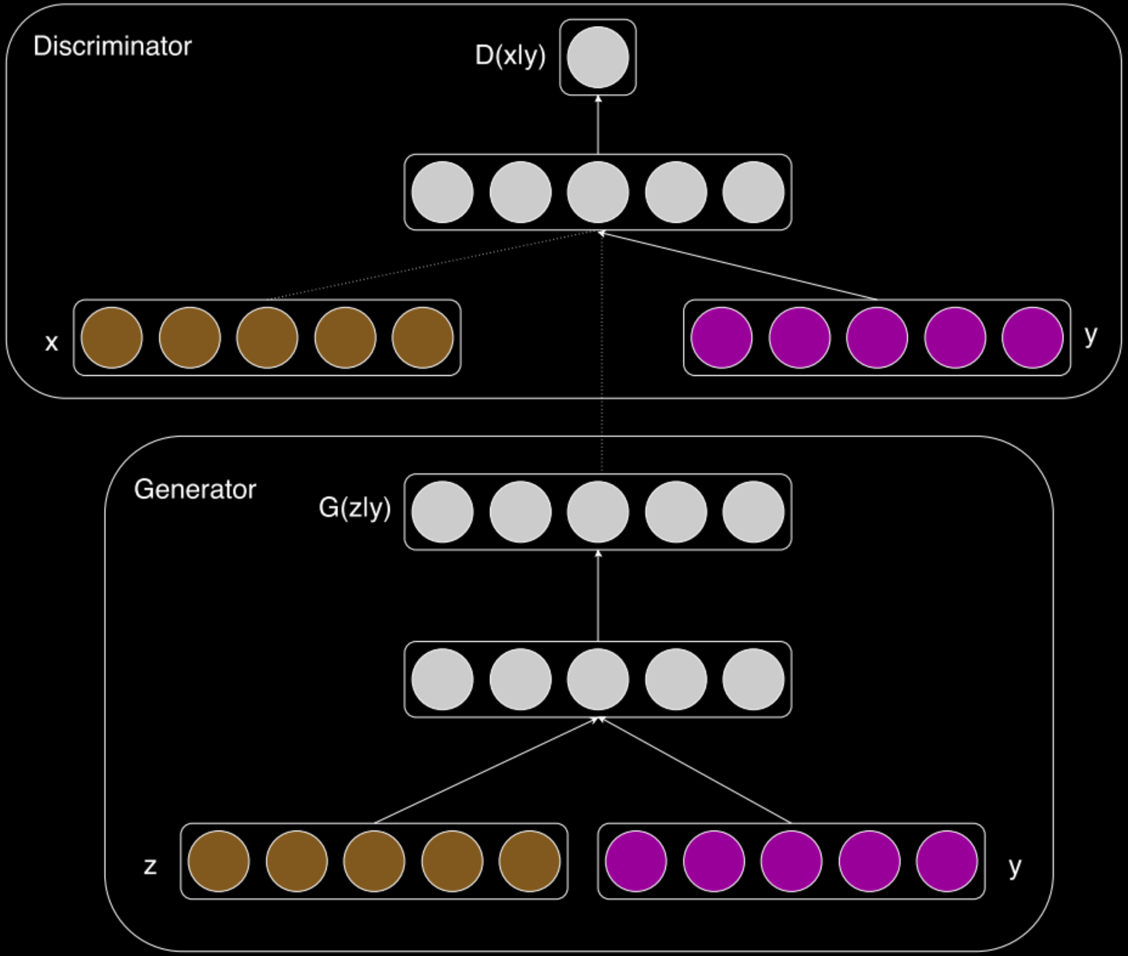

Figure 1 from[1]: Conditional adversarial net

Figure 2 from[1]: Generated MNIST digits, each row conditioned on one label

[1]**Mirza, M., & Osindero, S.** Conditional generative adversarial nets. *arXiv preprint* (2014). https://doi.org/10.48550/arXiv.1411.1784

Pix2Pix (Image-to-image translation with conditional adversarial networks)

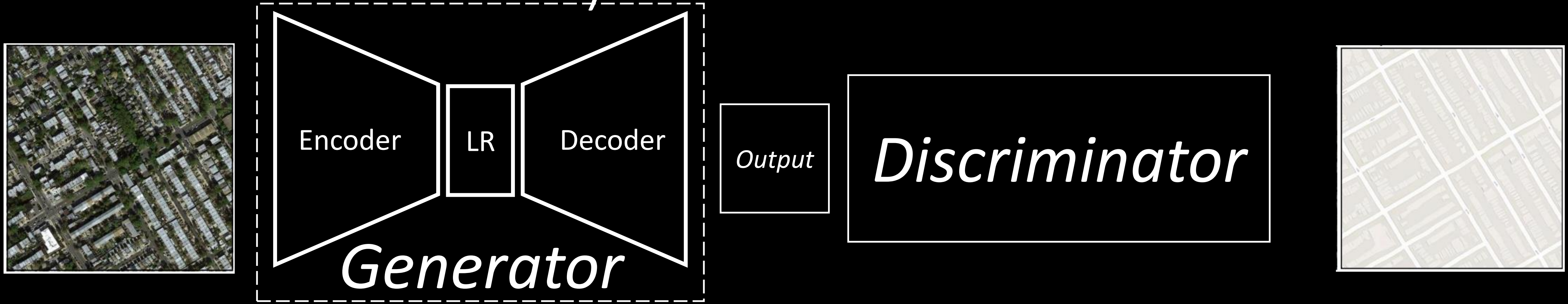

Figure 8 from[1]: Example results on Google Maps at 512x512 resolution (model was trained on images at 256 × 256 resolution, and run convolutionally on the larger images at test time). Contrast adjusted for clarity.

[1]**Isola, P., Zhu, J.-Y., Zhou, T., & Efros, A. A.** Image-to-image translation with conditional adversarial networks. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR 2017)*, 5967–5976 (2017). https://doi.org/10.1109/CVPR.2017.632

Pix2Pix (Image-to-image translation with conditional adversarial networks)

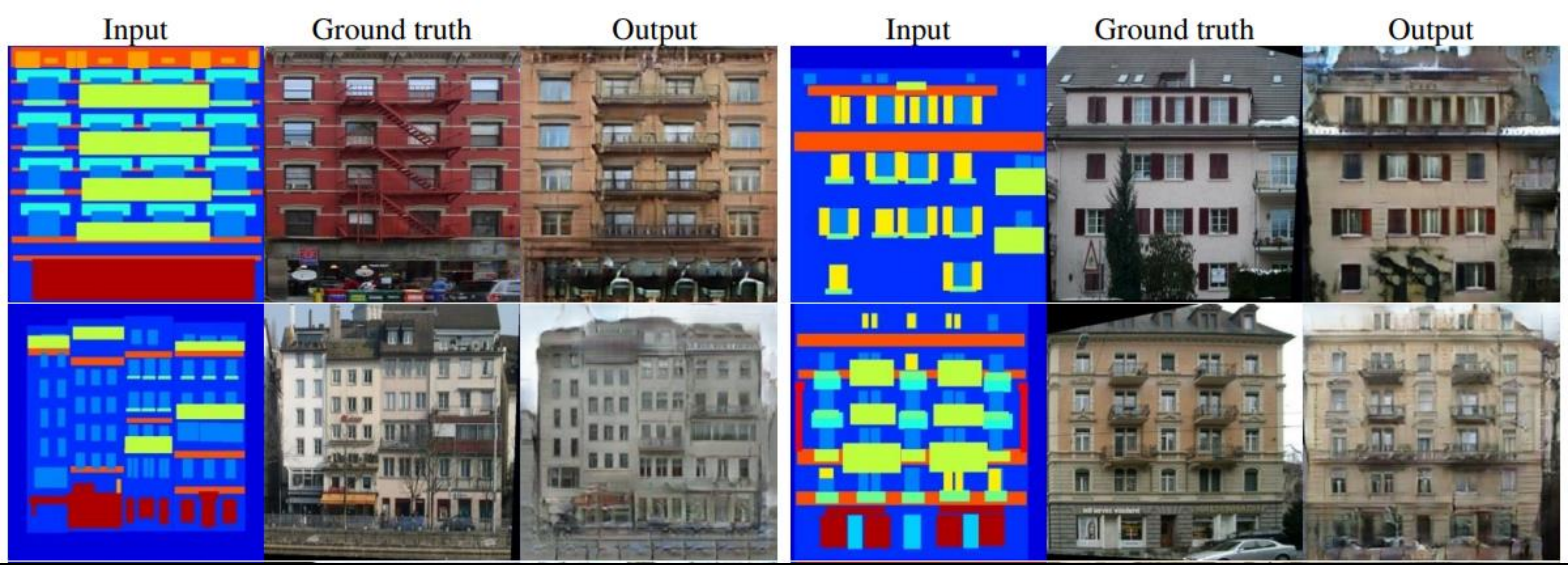

Figure 14 from[1]: Example results of our method on facades labels→photo, compared to ground truth.

[1]**Isola, P., Zhu, J.-Y., Zhou, T., & Efros, A. A.** Image-to-image translation with conditional adversarial networks. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR 2017)*, 5967–5976 (2017). https://doi.org/10.1109/CVPR.2017.632

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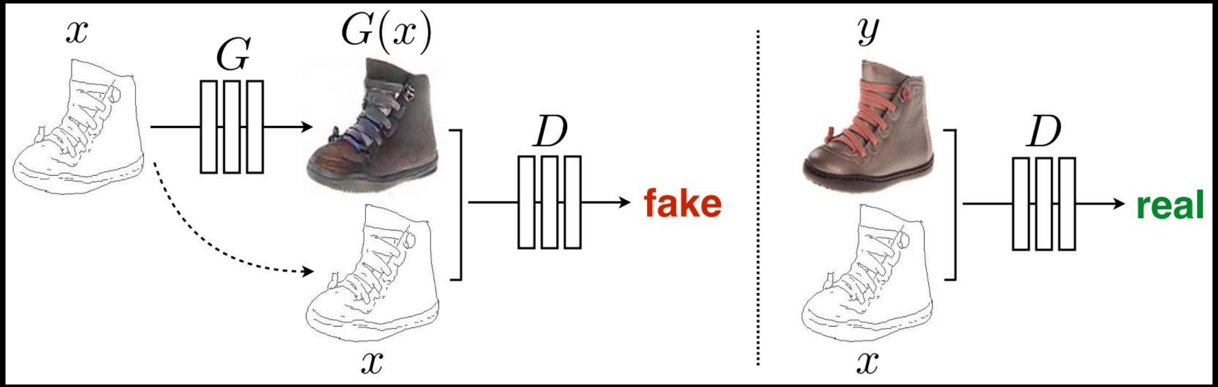

Figure 2 from[1]: Training a conditional GAN to map edges→photo.

Figure 16 from[1]: Example results of our method on automatically detected edges→handbags, compared to ground truth.

[1]**Isola, P., Zhu, J.-Y., Zhou, T., & Efros, A. A.** Image-to-image translation with conditional adversarial networks. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR 2017)*, 5967–5976 (2017). https://doi.org/10.1109/CVPR.2017.632

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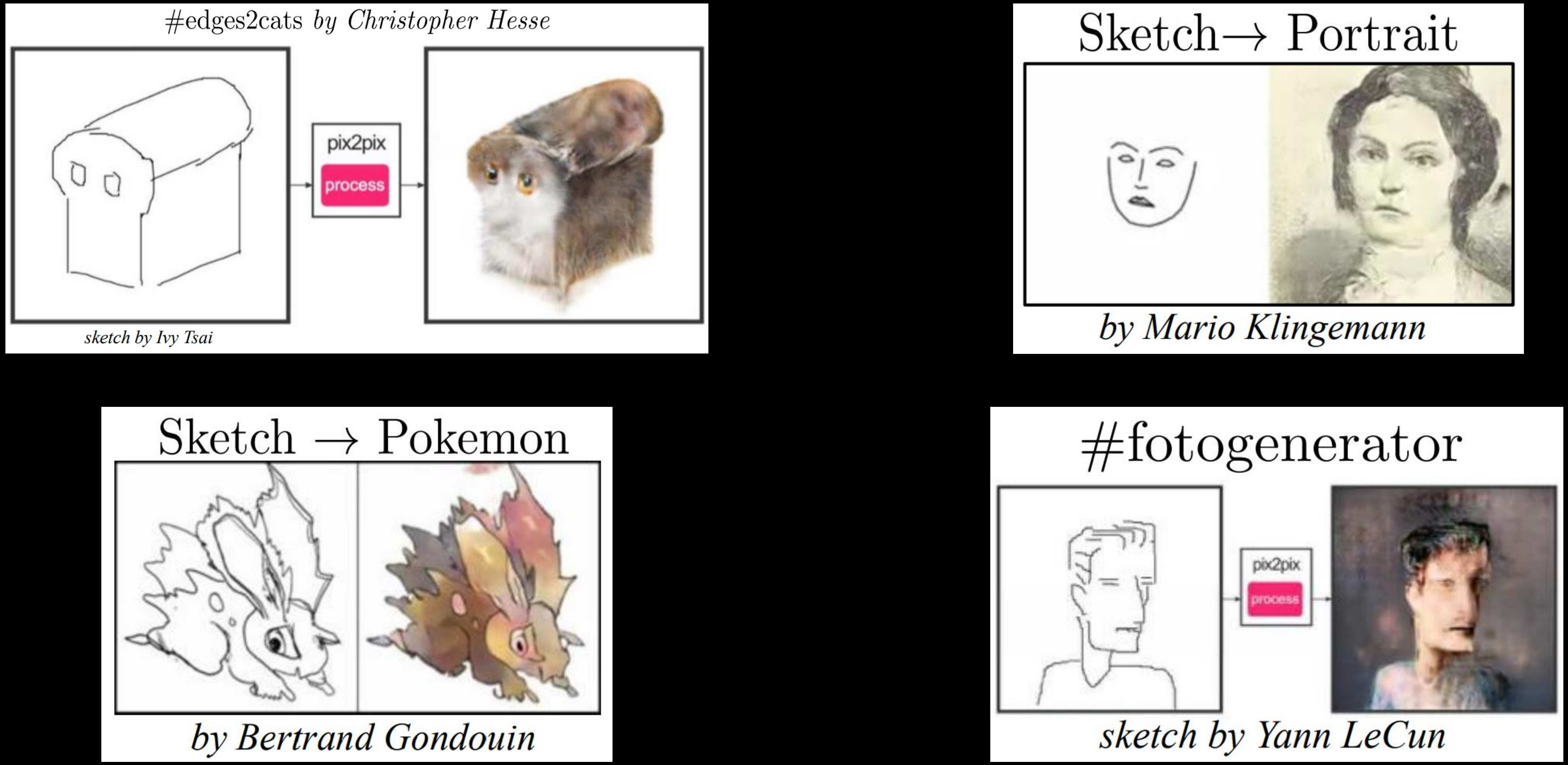

Figure 11 from[1]: Example applications developed by online community based on our pix2pix codebase

[1]**Isola, P., Zhu, J.-Y., Zhou, T., & Efros, A. A.** Image-to-image translation with conditional adversarial networks. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR 2017)*, 5967–5976 (2017). https://doi.org/10.1109/CVPR.2017.632

CycleGAN (Unpaired image-to-image translation using cycle-consistent adversarial networks)

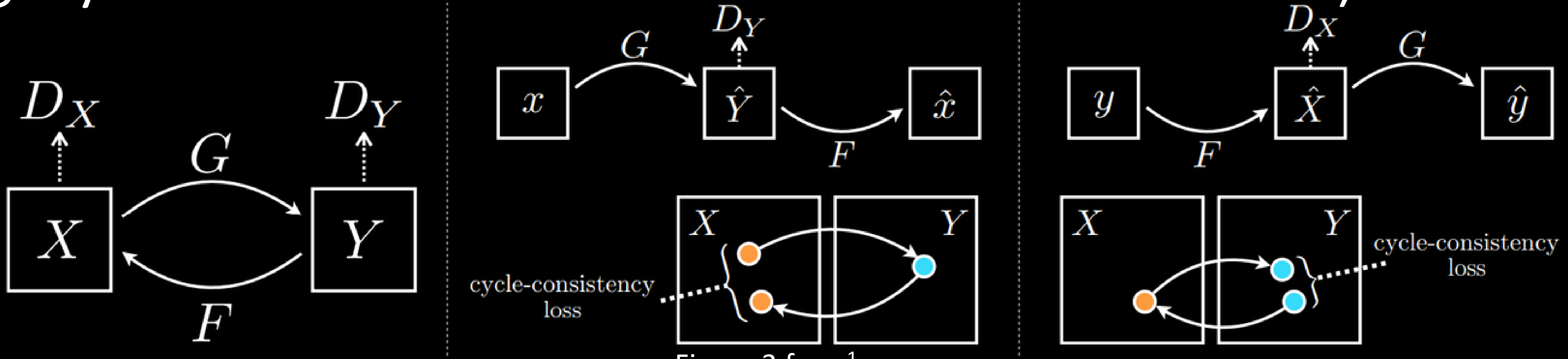

Figure 3 from[1]

Figure 1 from[1]

[1]**Zhu, J.-Y., Park, T., Isola, P., & Efros, A. A.** Unpaired image-to-image translation using cycle-consistent adversarial networks. *Proceedings of the IEEE International Conference on Computer Vision (ICCV 2017)*, 2223–2232. https://doi.org/10.1109/ICCV.2017.244

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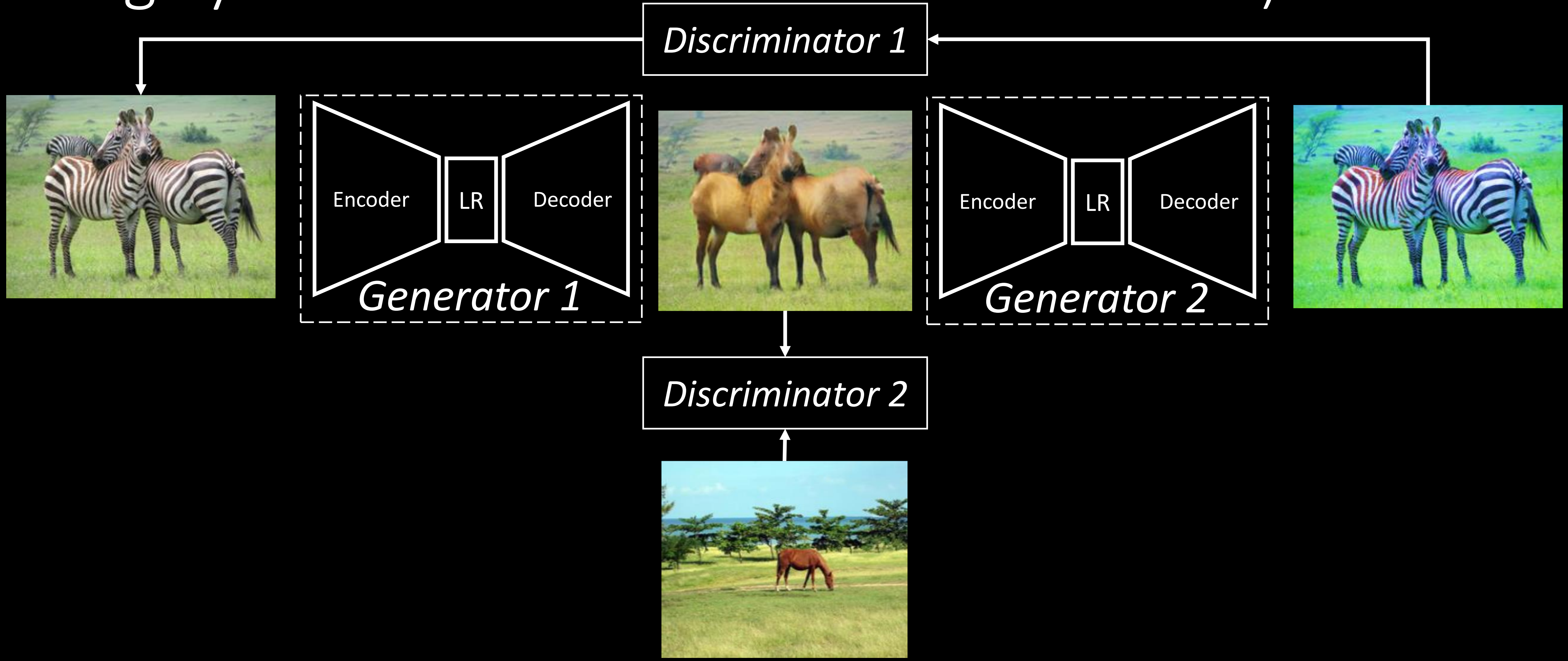

[1]**Zhu, J.-Y., Park, T., Isola, P., & Efros, A. A.** Unpaired image-to-image translation using cycle-consistent adversarial networks. *Proceedings of the IEEE International Conference on Computer Vision (ICCV 2017)*, 2223–2232. https://doi.org/10.1109/ICCV.2017.244

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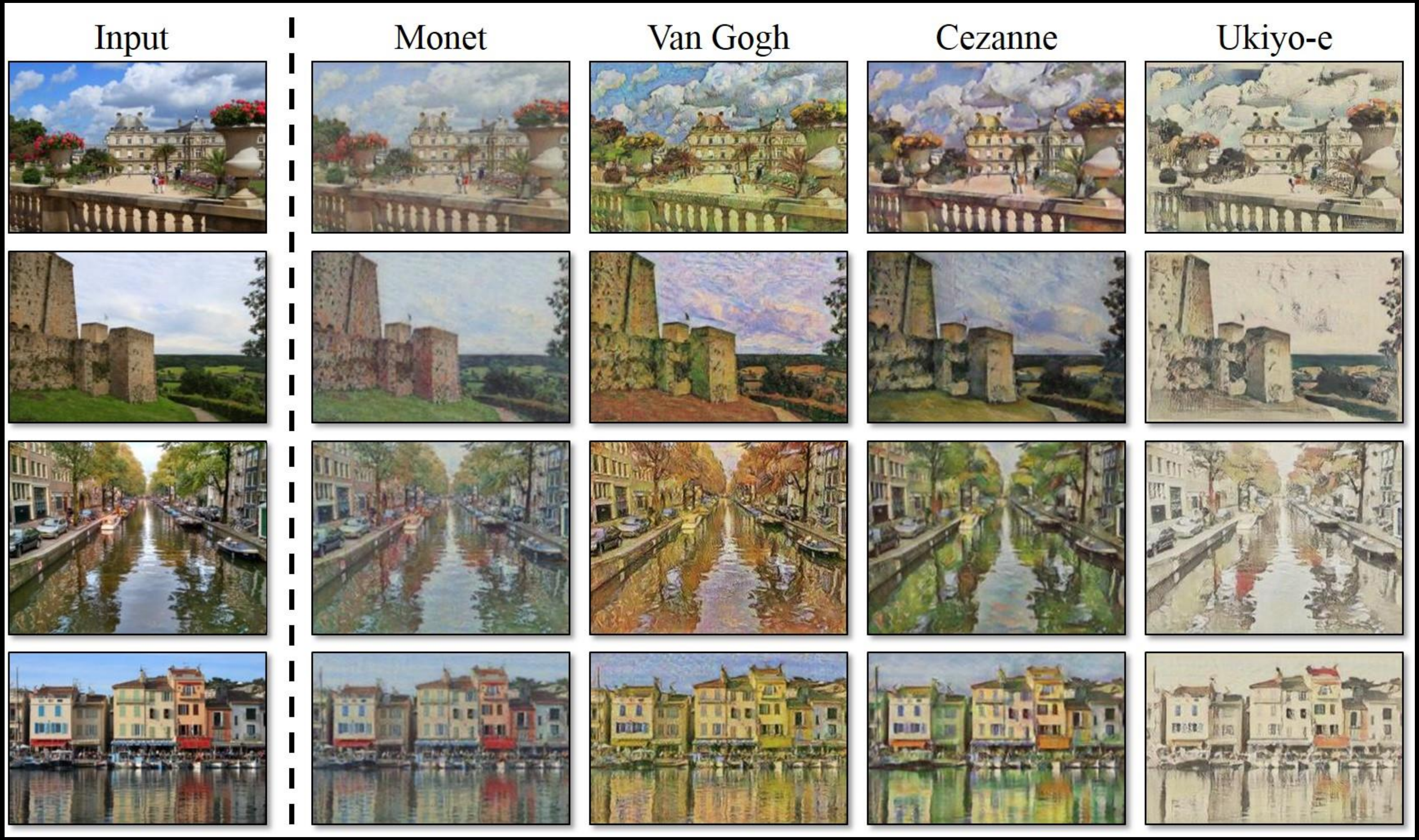

Figure 10 from[1] :Collection style transfer I: transfer input images into the artistic styles of Monet, Van Gogh, Cezanne, and Ukiyo-e.

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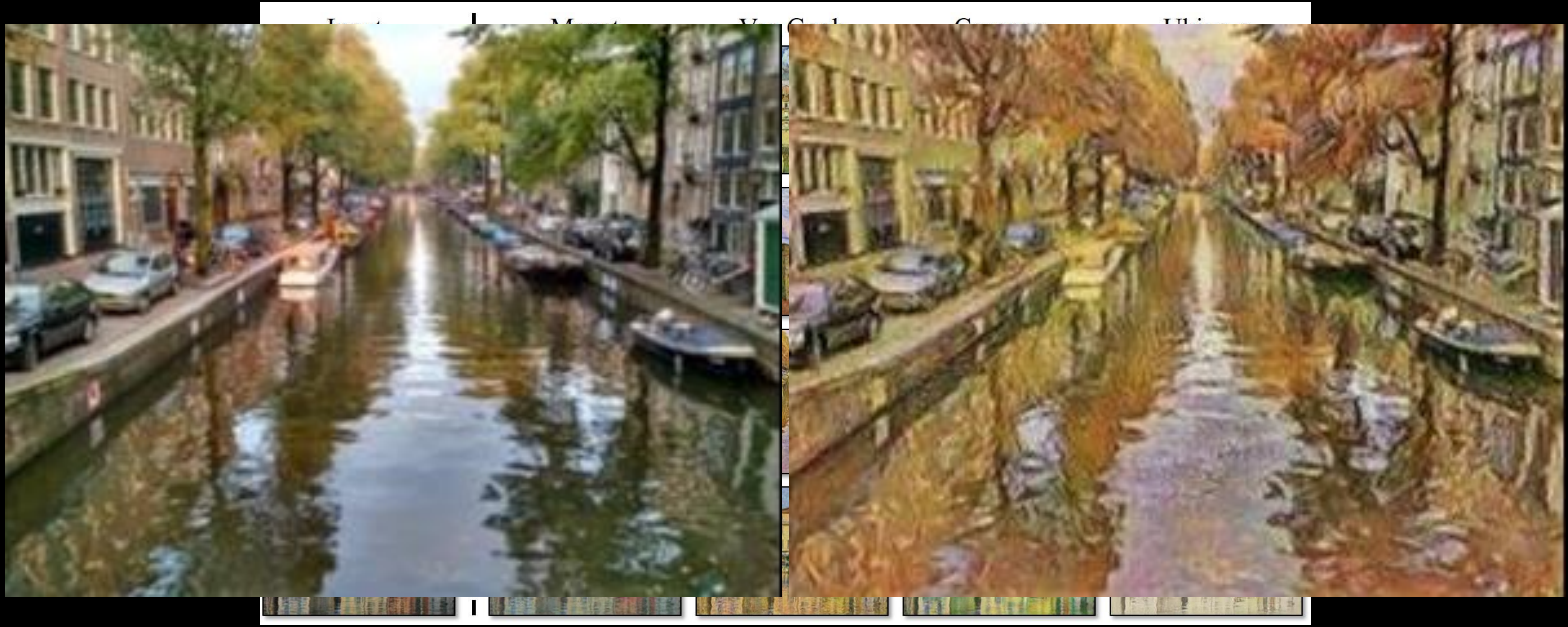

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StyleGAN

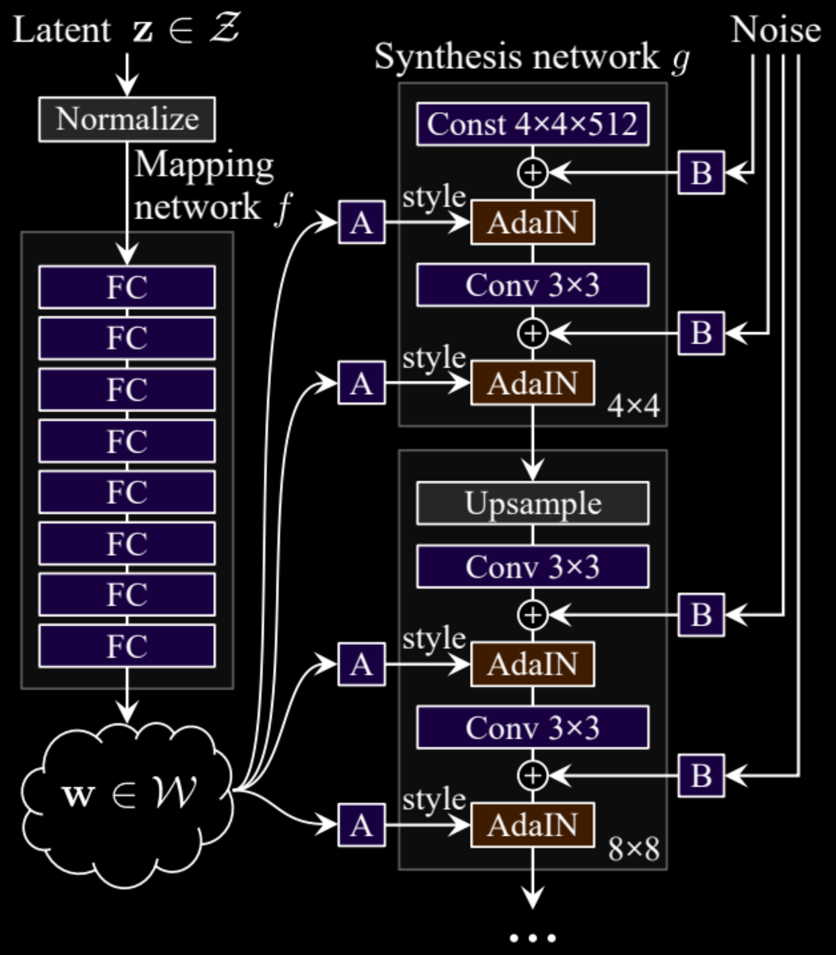

Figure 1 (b) from[1]. Style-based generator

Figure 2 from[1]. Uncurated set of images produced by our style-based generator (config F) with the FFHQ dataset.

[1]**Karras, T., Laine, S., & Aila, T.** A style-based generator architecture for generative adversarial networks. *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR 2019)*, 4401–4410. https://doi.org/10.1109/CVPR.2019.00453

Applications of GAN

Table 1 from[1]. Key studies that define different GAN applications.

Type	Authors [Ref]	Year	Model	Application
3 D object generation	Yu Y.et al. (Yu et al., 2020)	2020	GAN Point encoder	Processes unstructured data with no labelling
	Y Chen et al. (Chen et al., 2018)	2018	3D-CNN	Create sharp images of good quality
	G Ye et al. (Ye et al., 2020)	2020	Deep learning-based GAN	Improving 2D monochromatic images
	Q Ma et al. (Ma et al., 2020)	2020	Generative 3D model	Human motion capturing
	Y Jin et al. (Jin et al., 2020)	2020	GAN model with three-tier adversarial principle	Production of high-quality 3D objects
Medicine	S Baek et al. (Baek et al., 2020)	2020	GAN and Mesh Model	Production of MR Images in sealed pixels
	Jain D K et al. (Jain et al., 2020)	2020	GAN poser	Detection of human motion
	A Teramoto et al. (Teramoto et al., 2020)	2020	Deep convolutional neural network (DCCN) with GAN	Classify cytological images
	M D Cirillo et al. (Cirillo et al., 2020)	2020	Vox2Vox: 3D-GAN	Brain tumour segmentation
	H C Shin et al. (Shin et al., 2018)	2018	Conventional GAN	Identify medical images
	J. Islam et al. (Islam & Zhang, 2020)	2020	Conventional GAN	Brain image generation
	H Lan et al. (Lan & Toga, 2020)	2020	SC-GAN	NeuroImage synthesis
	G Zhaoa (Zhaoa, 2020)	2020	Bayesian Conditional GAN	MRI Brain Image Synthesis
	R Oulbacha et al. (Oulbacha & Kadoury, 2020)	2020	Pseudo-3D Cycle GAN	MRI to CT Synthesis of the Lumbar Spine
	X Zhang et al. (X. Zhang et al., 2020)	2020	Deform-GAN	Noise reduction in 3D medical images
	D Yang et al. (Yang et al., 2019)	2019	Adversarial image-to-image networks	Medical image synthesis and semantic segmentation
Pandemics	Loey M et al. (Loey et al., 2020)	2020	GAN and deep transfer learning	COVID-19 detection with chest images
	S Albahli (Albahli, 2020)	2020	GAN with the deep neural network model	Diagnose coronavirus disease pneumonia
Image processing	C Li et al. (Li & Wand, 2016)	2016	Markovian GAN	Generate 3D image from 2D image
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	T Go et al. (Go et al., 2020)	2020	Deep neural network-based GAN	Perform image transformation
	S Zhang et al. (S. Zhang et al., 2020)	2020	Conventional GAN	Image denoising
	H Tang et al. (Tang et al., 2020)	2020	Conventional GAN	Semantic guided scene generation
Face detection	F Mokhayeri et al. (Mokhayeri et al., 2020)	2020	A new Controllable GAN (C-GAN	Cross-domain face synthesis
	J Zhao et al. (Zhao et al., 2019)	2019	Dual-Agent Generative Adversarial Network (DA-GAN)	Unconstrained Face Recognition
	M Kowalski et al. (Kowalski et al., 2020)	2020	Deep learning-based GAN	Face Image Generation
	D P Jaiswal et al. (Jaiswal et al., 2020)	2020	Conventional GAN	Face animation
Text transferring	L Sixt et al. (Sixt et al., 2019)	2019	Conventional GAN	Generating realistic labelled data
	R Spick et al. (Spick et al., 2020)	2020	3D-GAN	Generate high-quality texture by adding colour
Traffic control	D Xu et al. (Xu et al., 2020)	2020	GE-GAN	Road traffic estimation
	Fathi-Kazerooni S et al. (Beery et al., 2020)	2020	GAN Tunnel	Detection of traffic images

[1]**Aggarwal, A., Mittal, M., & Battineni, G.** Generative adversarial network: An overview of theory and applications. *International Journal of Information Management Data Insights*, **1**(1), 100004 (2021). https://doi.org/10.1016/j.jjimei.2020.100004

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	A Teramoto et al. (Teramoto et al., 2020)	[illegible]	[illegible]	[illegible]
	M D Cirillo et al. (Cirillo et al., 2020)	[illegible]	[illegible]	[illegible]
	H C Shin et al. (Shin et al., 2018)	[illegible]	[illegible]	[illegible]
	J. Islam et al. (Islam & Zhang, 2020)	[illegible]	[illegible]	[illegible]
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	Fathi-Kazerooni S et al. (Beery et al., 2020)	2020	GAN Tunnel	Detection of traffic images

Identify medical images

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	H C Shin et al. (Shin et al., 2018)	[illegible]	[illegible]	[illegible]
	J. Islam et al. (Islam & Zhang, 2020)	[illegible]	[illegible]	[illegible]
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	R Spick et al. (Spick et al., 2020)	2020	3D-GAN	Generate high-quality texture by adding colour
Traffic control	D Xu et al. (Xu et al., 2020)	2020	GE-GAN	Road traffic estimation
	Fathi-Kazerooni S et al. (Beery et al., 2020)	2020	GAN Tunnel	Detection of traffic images

Brain image generation

[1]**Aggarwal, A., Mittal, M., & Battineni, G.** Generative adversarial network: An overview of theory and applications. *International Journal of Information Management Data Insights*, **1**(1), 100004 (2021). https://doi.org/10.1016/j.jjimei.2020.100004

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	S Albahli (Albahli, 2020)		model	pneumonia
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COVID-19 detection with chest images

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Traffic control	D Xu et al. (Xu et al., 2020)	2020	GE-GAN	Road traffic estimation
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Generate 3D image from 2D image

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Applications of GAN in Astronomy

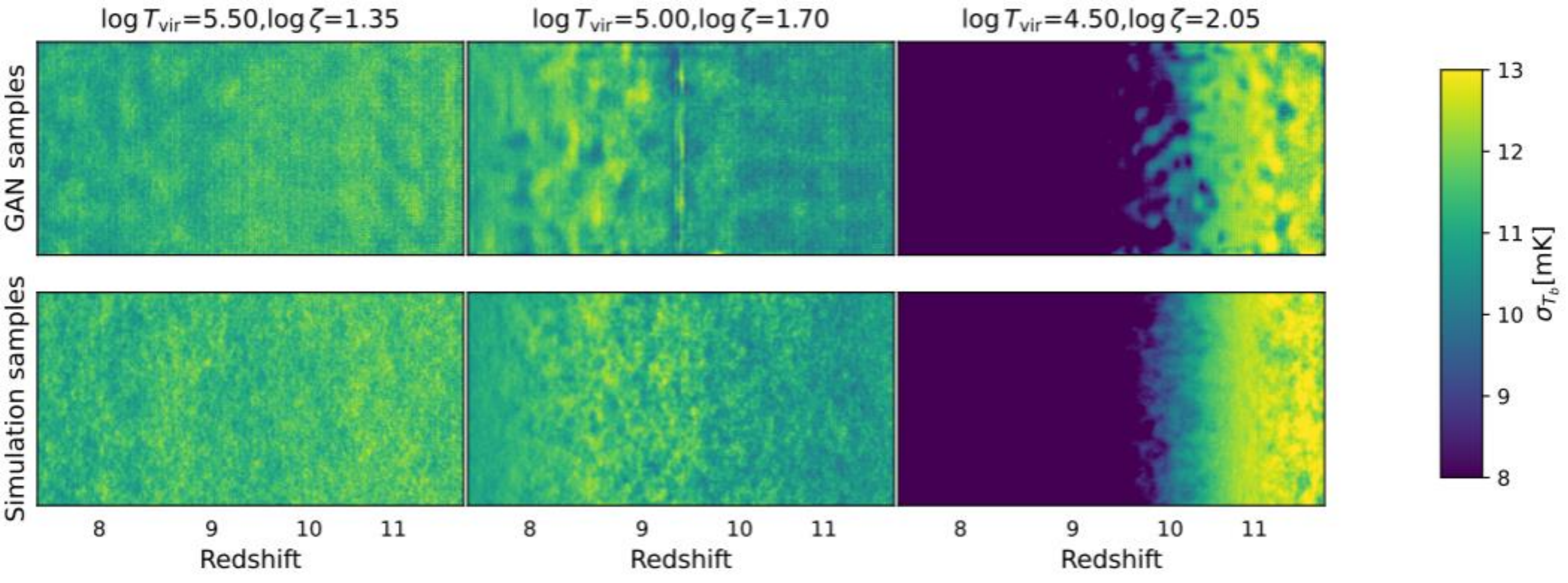


Figure 14 from[1]. The standard deviation of the 21 cm brightness temperature map for each pixel over 1,024 image samples of the large-scale GAN (top), in comparison with the simulated images using 21cmFAST (bottom).

[1]**Diao, K., & Mao, Y.** Multi-fidelity emulator for large-scale 21 cm lightcone images: a few-shot transfer learning approach with generative adversarial network. *arXiv preprint* (2025). https://doi.org/10.48550/arXiv.2502.04246

Applications of GAN in Astronomy

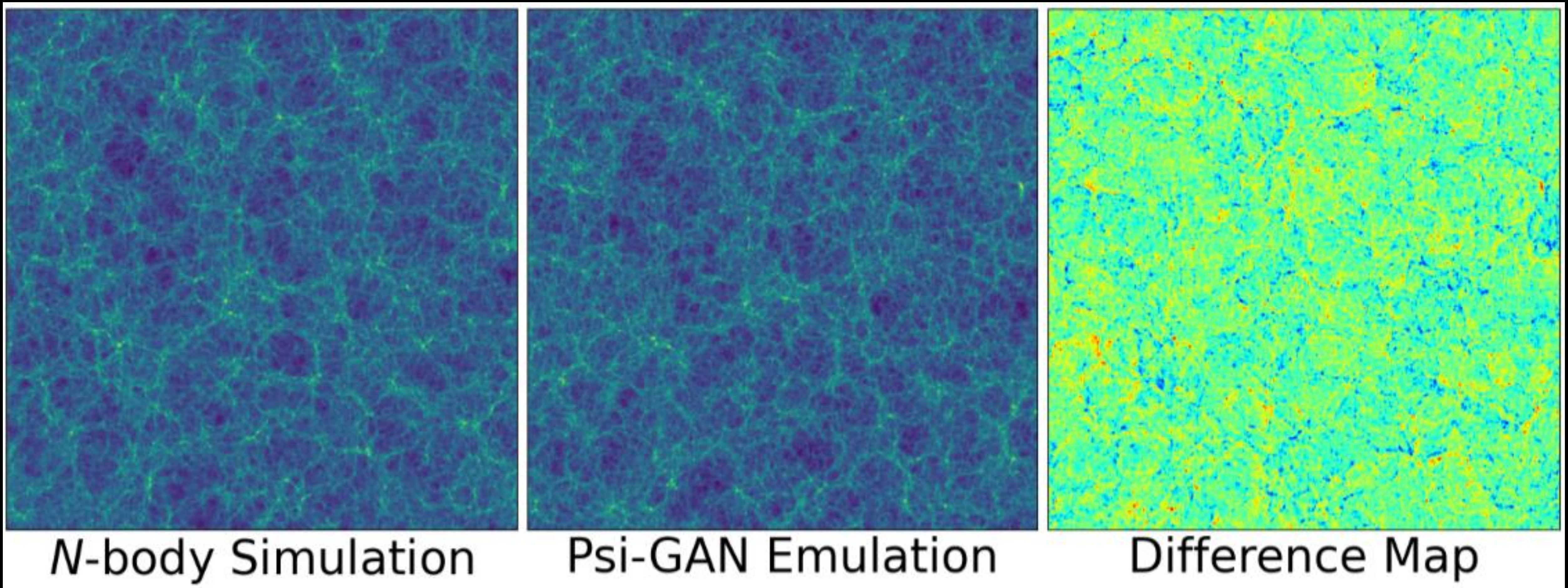


Figure 10 from[1]. An example showing the the dark matter distribution field from an N-body simulation (left) and an emulation generated by Psi-GAN (centre), the difference map (right), showing the differences between the N-body simulation and the Psi-GAN emulation.

[1] **Bhambra, P., Joachimi, B., Lahav, O., et al.** PSI-GAN: a power-spectrum-informed generative adversarial network for the emulation of large-scale structure maps across cosmologies and redshifts. *Monthly Notices of the Royal Astronomical Society*, **536**(3), 3138–3157 (2025). https://doi.org/10.1093/mnras/stae2810

Applications of GAN in Astronomy

GANDALF: **G**enerative **A**dversaria **N**etworks for **D**isentangling and **L**earning **F**ramework

A frame from The Lord of the Rings: The Fellowship of the Ring (2001), directed by Peter Jackson, New Line Cinema.

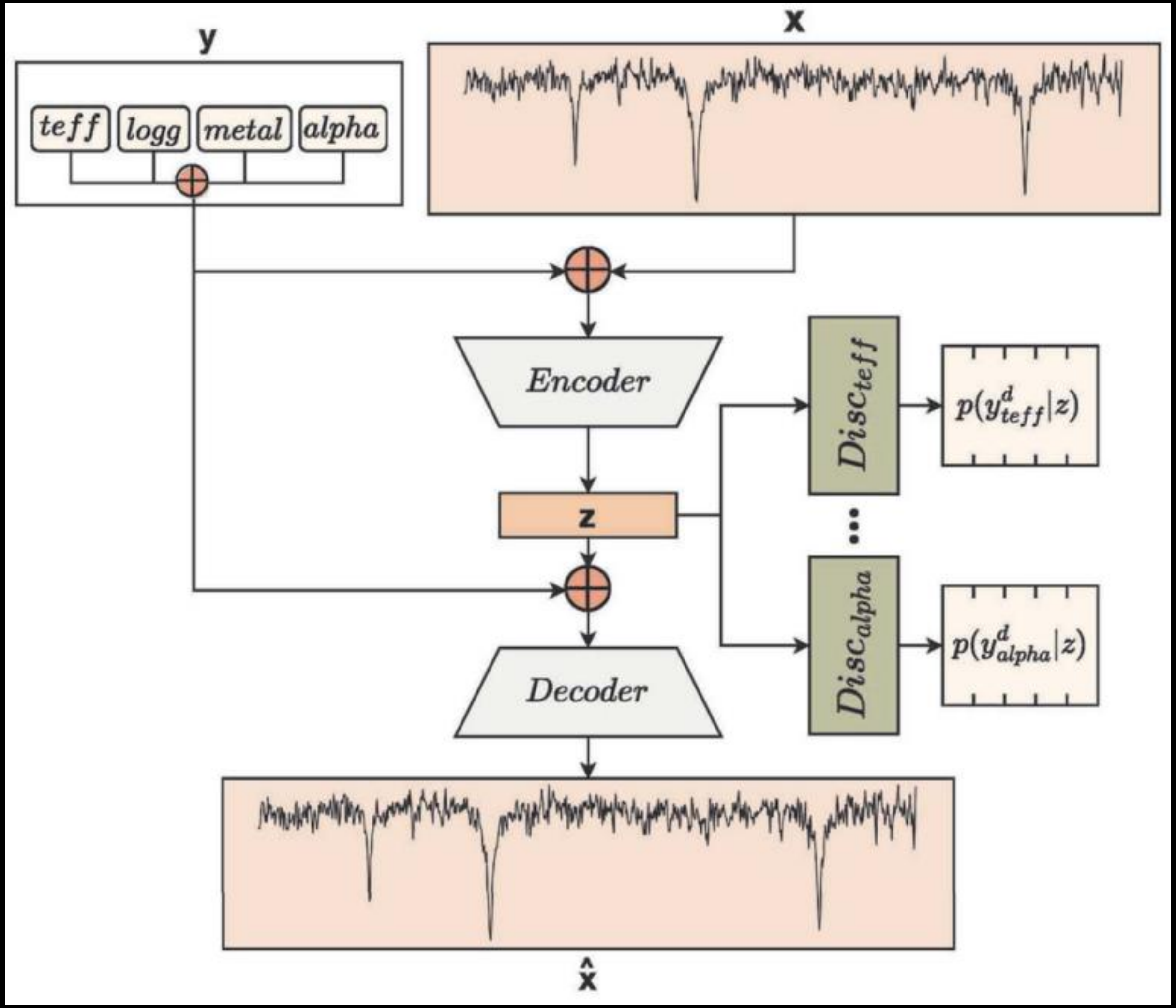


Figure 1 from[1]. The disentanglement architecture featuring multi-discriminators

[1]**Manteiga, M., Santoveña, R., Álvarez, M. A., et al.** A method based on Generative Adversarial Networks (GANs) for disentangling atmospheric properties in astronomical spectra. *arXiv preprint* (2025). https://doi.org/10.48550/arXiv.2501.11762

The GAN is dead; long live the GAN!

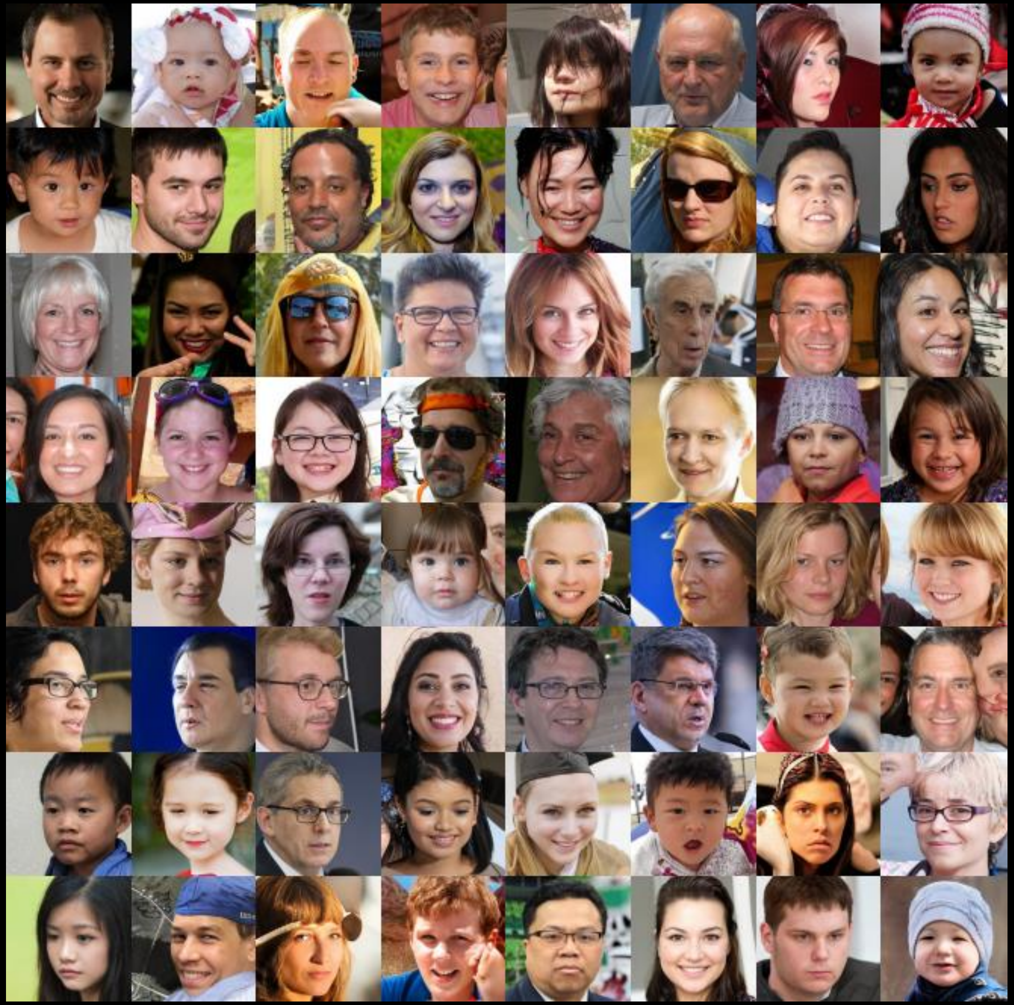
The GAN is dead; long live the GAN! A Modern Baseline GAN

Yiwen Huang Brown University
Aaron Gokaslan Cornell University
Volodymyr Kuleshov Cornell University
James Tompkin Brown University

Abstract

There is a widely-spread claim that GANs are difficult to train, and GAN architectures in the literature are littered with empirical tricks. We provide evidence against this claim and build a modern GAN baseline in a more principled manner. First, we derive a well-behaved regularized relativistic GAN loss that addresses issues of mode dropping and non-convergence that were previously tackled via a bag of ad-hoc tricks. We analyze our loss mathematically and prove that it admits local convergence guarantees, unlike most existing relativistic losses. Second, this loss allows us to discard all ad-hoc tricks and replace outdated backbones used in common GANs with modern architectures. Using StyleGAN2 as an example, we present a roadmap of simplification and modernization that results in a new minimalist baseline—R3GAN ("Re-GAN"). Despite being simple, our approach surpasses StyleGAN2 on FFHQ, ImageNet, CIFAR, and Stacked MNIST datasets, and compares favorably against state-of-the-art GANs and diffusion models. Code: https://www.github.com/brownvc/R3GAN

https://github.com/brownvc/R3GAN



Qualitative examples of sample generation from R3GAN on FFHQ-256

Huang, Y., Gokaslan, A., Kuleshov, V., & Tompkin, J. The GAN is dead; long live the GAN! A Modern GAN Baseline. *arXiv preprint* (2025). https://doi.org/10.48550/arXiv.2501.05441

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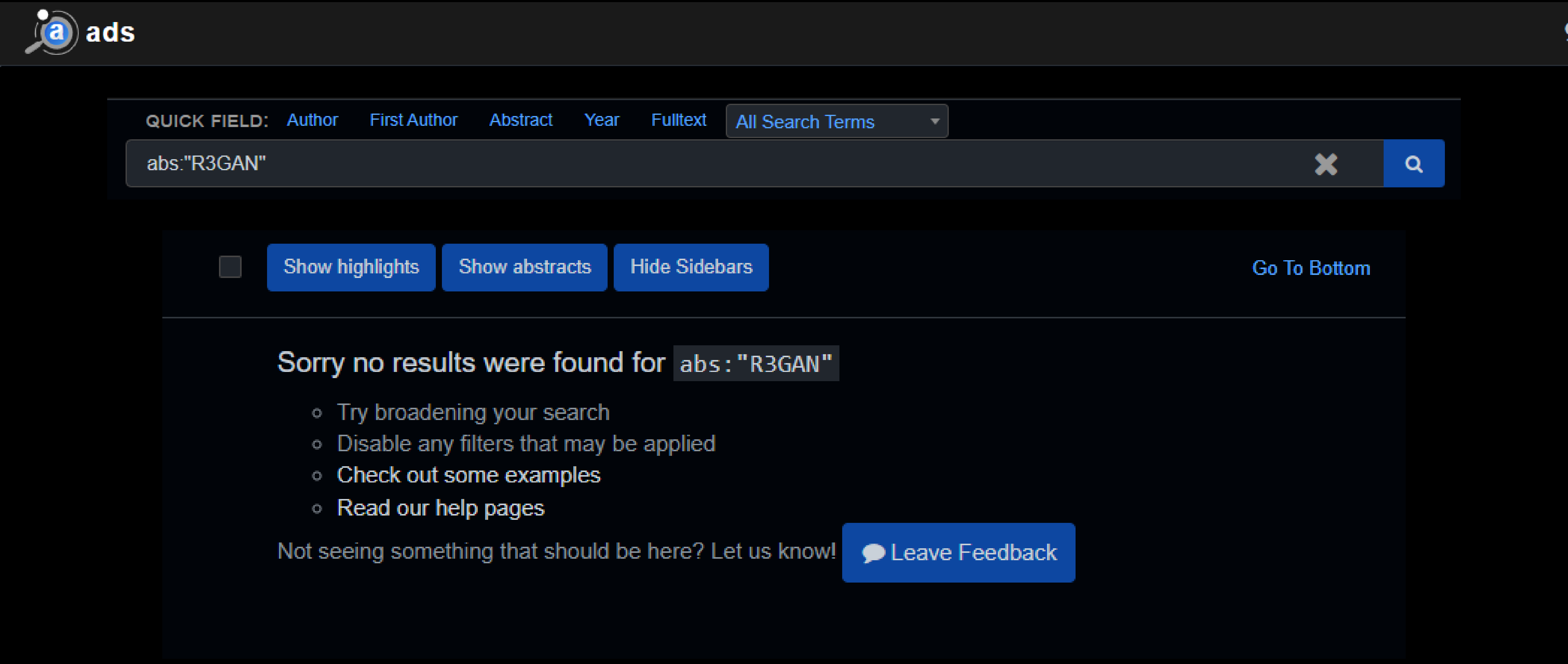
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abs:"R3GAN"
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Ethics and Limitations of Using Generative Models

1. Ethical Risks of Generative Models

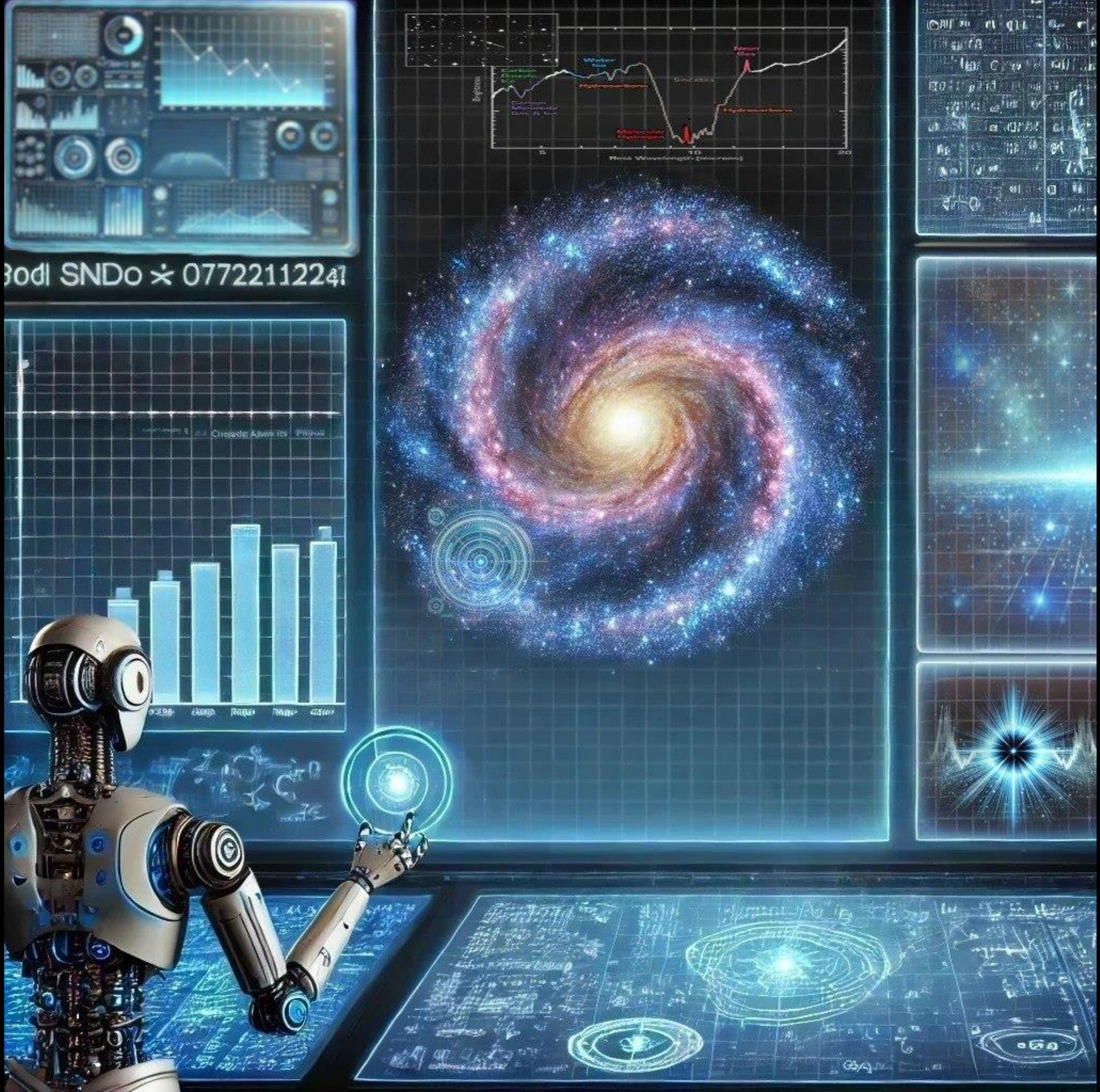
- **Spread of misinformation**: Generative models can create fake texts, images, and videos, which threatens trust in information.
- **Copyright infringement**: Models can generate content that violates the rights of original creators.
- **Discrimination and bias**: Models can reproduce and amplify stereotypes present in the training data.

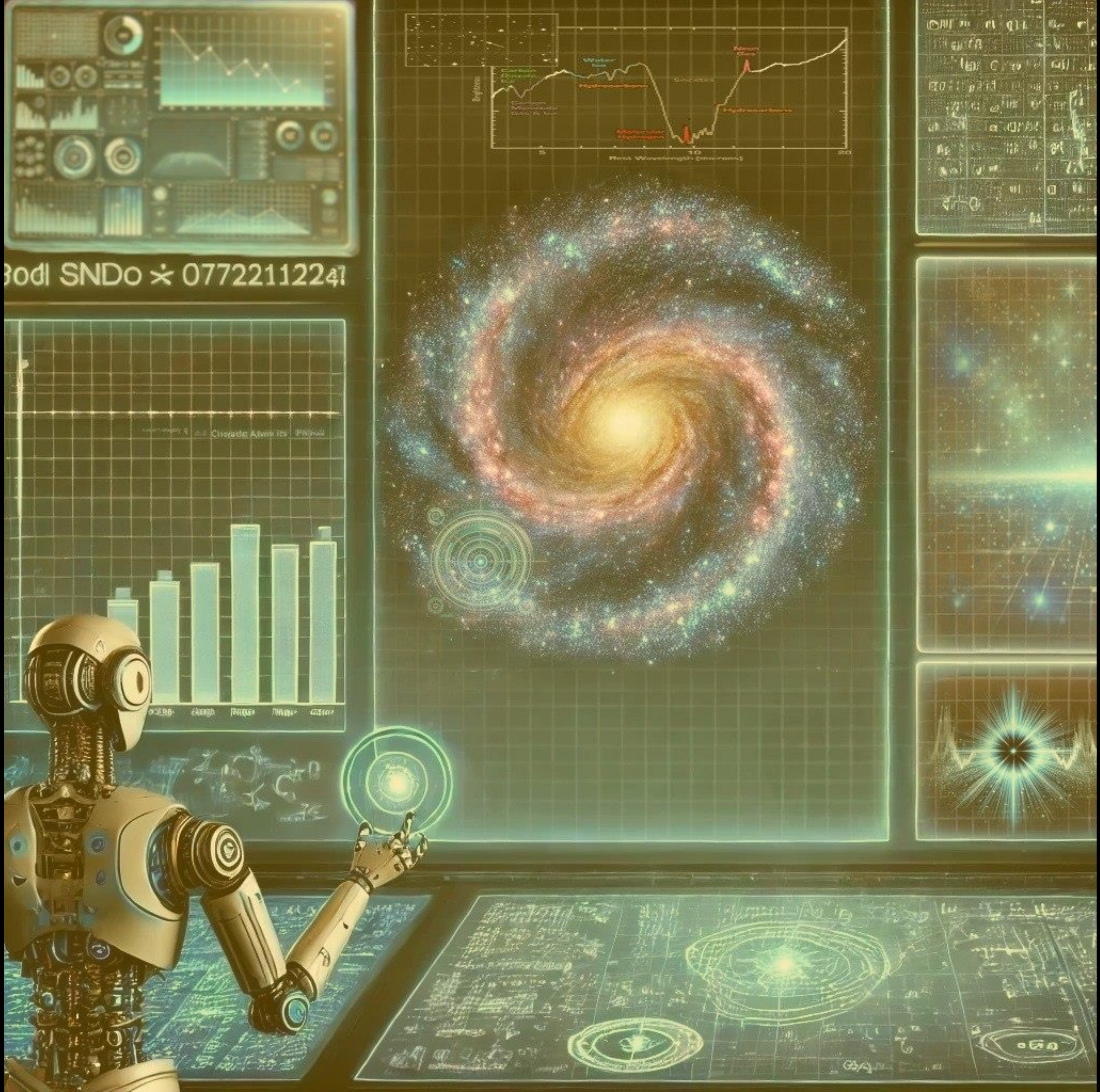
2. Limitations of Generative Models

- **Lack of context understanding**: Models don’t have consciousness and may generate incorrect or harmful content.
- **Data dependency**: The quality of generation depends directly on the quality and representativeness of the training data.
- **High energy consumption**: Training and using generative models require significant computational resources, impacting the environment.

3. Responsible Use

- **Transparency**: Clearly indicate when content is created using AI.
- **Quality control**: Check generated content to ensure it meets ethical standards.
- **Regulation**: Develop and follow legal and ethical guidelines for AI use.



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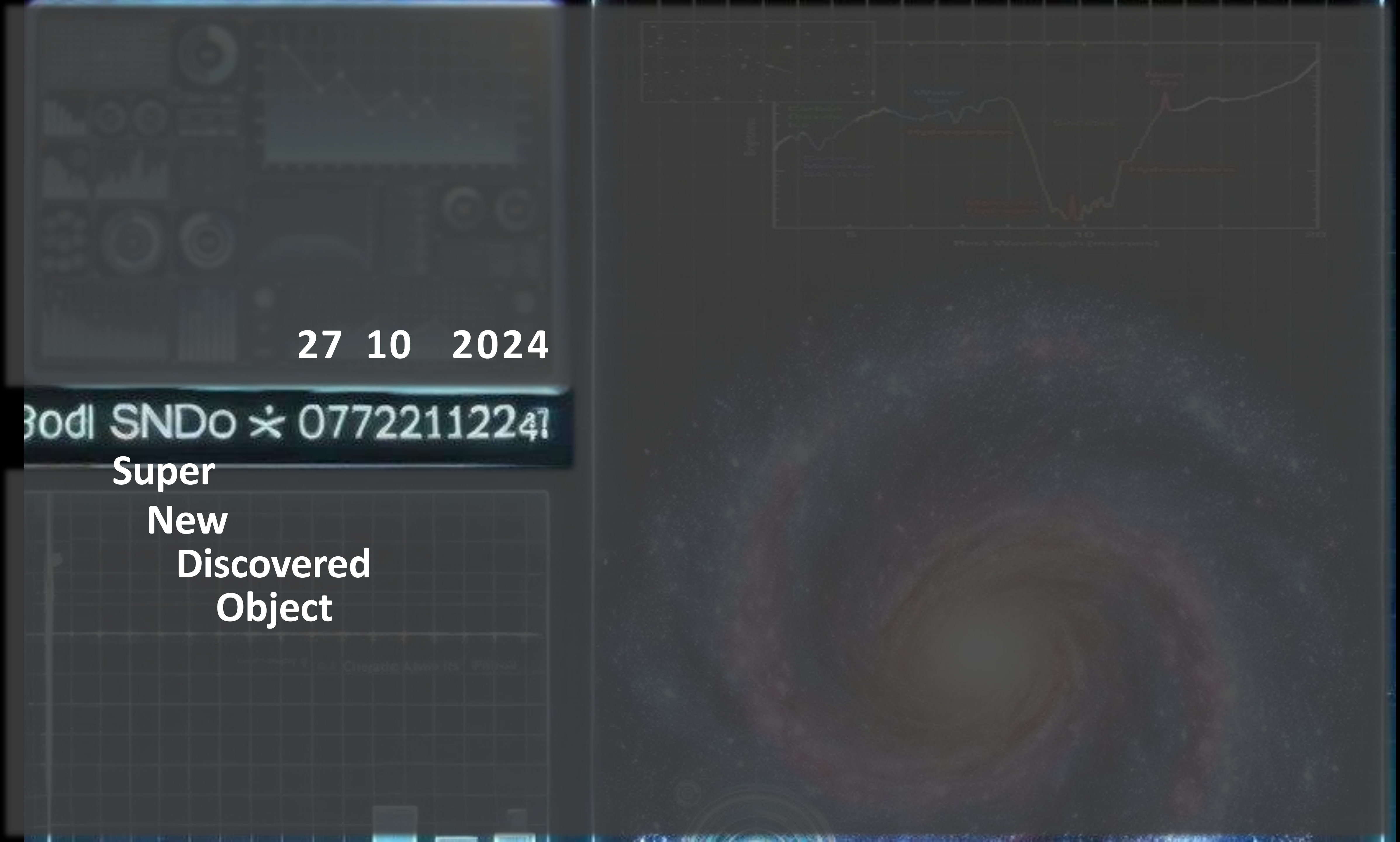

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Super
New
Discovered
Object

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Super New Discovered Object

Thank you for attention